Relevance Feedback in Surfimage

Christophe Meilhac, Matthias Mitschke,* and Chahab Nastar

INRIA
BP 105
F-78153 Le Chesnay, France
email: Chahab.Nastar@inria.fr
web demo: http://www-syntim.inria.fr/htbin/syntim/surfimage/surfimage.cgi

Abstract

Relevance feedback is one of the strong components of Surfimage, the INRIA content-based image retrieval system. Relevance feedback is about learning from user interaction, and is useful in tasks like query refinement and multiple queries. We present two relevance feedback techniques currently implemented in Surfimage.

1 Introduction

There are several reasons why one would like to have a relevance feedback module in an image retrieval engine. The main one is flexibility, i.e. the ability for the system to adapt to a situation (user, context...) in order to satisfy a specific – yet subjective – goal.

Surfimage [3, 4] includes a relevance feedback module which can be used by the user to define over the interactions a set of relevant and a set of nonrelevant images to their query.

We describe two relevance feedback techniques currently implemented in Surfimage. While the first method tries to answer the find me more question by robust parametric density estimation [2], a second method uses nonparametric density estimation and Bayes decision rule for structuring all items in the database as relevant or nonrelevant to the query [1]. Both methods are briefly presented hereafter.

2 First method

We first note that in both methods, several features are combined, spanning a large feature space that should capture various aspects of image content [2].

The first method is described in details in [2]. The main idea is to integrate both the positive (relevant) and the negative (nonrelevant) examples of the user in a common parametric density estimation technique. Assuming independence, the estimation is performed over each feature component. The estimated density should be representative of as many relevant and as few nonrelevant items as possible. A dedicated error count is minimized and ensures robustness to outliers.

Once the density is estimated, it is sampled, and the database is looked up for nearest neighbors to the sample. This technique will retrieve more “varied” images than the classic maximum likelihood estimator and is shown to be more powerful than the classic relevance feedback adapted from information retrieval.

One of the nice properties of the algorithm is that, in cases where relevant and nonrelevant images are all mixed up within a feature component, the estimated distribution will tend to be flat, inferring that the corresponding feature component is not discriminant for the query.

3 Second method

Unlike the first method, our more recent relevance feedback technique uses a posterior model [1].

The goal here is to estimate both the relevant and the nonrelevant densities using nonparametric density estimation. Thus, the database is partitioned into relevant, nonrelevant or ambiguous items, with respect to the query. Over user interactions, the partition is improved; in particular, several search strategies are offered for dealing with ambiguities and improving the system estimation of user intentionality. Depending on the application, the method allows for selectively controlling precision (as few false alarms as possible) or recall (as few misses as possible). System performance is shown to improve over the iterations.

Due to nonparametric multimodal estimation, multiple queries are fully operational, irrespective of the cross-similarity between queries in feature space.
Figure 1: Correct classification of city scenes (the two images on top left have a green tag) versus “rest of the database” with relevance feedback. Note that the 14 other images are classified as nonrelevant (red tags).

We illustrate the method on a classification example in a homebrew database of 3670 images with varied content (textures, faces, paintings, landscapes and city scenes). The user is looking for city scenes. The total number of city scenes in the database is about 50. The user has labeled about 10 city scenes (relevant images) and 10 nonrelevant images. The system has then retrieved the images presented in figure 1. Note that on this figure the system has retrieved 2 city scenes and has classified them correctly (green tag on top left of the image) while the remaining images of the page are estimated to be nonrelevant (red tag on top left of the image).

4 Conclusion

We have presented relevance feedback in the Surfimage system. Relevance feedback is viewed as a density estimation problem. While a first model is parametric and uses a forward method, the second technique uses posterior probabilities and nonparametric estimation. Relevance feedback is one of the key components of Surfimage for better user interactivity, in particular for general public applications where the user cannot be assumed to have any expertise in image analysis.

Warning: The references are partial. They are only related to articles dealing with Surfimage. A recursive search on the referenced papers will lead to state-of-the-art articles on image retrieval and relevance feedback.

References


