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Signal Processing 85 (2005) 395–399
SIGNAL PROCESSING
www.elsevier.com/locate/sigpro

Short Communication

Adaptive relevance feedback based on Bayesian inference for image retrieval

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Received 1 August 2002; received in revised form 1 July 2004

Abstract

Relevance feedback can be considered as a Bayesian classification problem. For retrieving images efficiently, an adaptive relevance feedback approach based on the Bayesian inference, rich get richer (RGR), is proposed. If the feedback images in current iteration are consistent with the previous ones, the images that are similar to the query target are assigned to high probabilities. Therefore, the images that are similar to the user's ideal target are emphasized step by step. The experiments showed that the average precision of RGR improves 5–20% on each interaction compared with non-RGR. When compared with MARS, the proposed approach greatly reduces the user's efforts for composing a query and captures user's intention efficiently.

Keywords: Relevance feedback; Bayesian inference; Image retrieval

1. Introduction

Due to the rapid growing amount of digital images on World Wide Web, there is an urgent need for large multimedia database management. In the past few years, content-based image retrieval (CBIR) has become an active research area and many interesting image retrieval systems are beginning to appear on the Web [2,4,8,9,11,13]. One important component of these systems is a relevance feedback module. Relevance feedback is a process of automatically adjusting an existing query using the information feedback by the user [3,5–7,12,15]. The standard relevance feedback paradigm can be described as follows. First, the user submits a query and the system finds and displays a set of images that are relevant to the query. Then the user informs the system of which images are relevant or irrelevant. After that, the system adjusts the retrieval or query model to find more relevant images.

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0165-1684/$ - see front matter
doi:10.1016/j.sigpro.2004.10.006

Relevance feedback can be considered as a Bayesian classification problem, an interpretation that has previously been considered in the literature [1,14]. Cox et al. [1] applied the Bayesian learning technique to search target images. Vasconcelos et al. [14] proposed an alternative formulation to minimize the probability of retrieval error. In this paper, rich get richer (RGR) considers the image retrieval process as a problem of determining image's probabilities being relevant to the user's query intention. If the feedback images of current iteration are consistent with the previous ones, the images that are similar to the query target are guaranteed to have higher updated relevance probabilities. RGR can propagate user's feedback information into the retrieval process step by step. As a result, the relevant images will be retrieved rapidly. RGR is similar to the method proposed by Cox et al. [1] and by Vasconcelos et al. [14], but with two differences. In RGR, the class conditional densities are changed in each feedback, whereas in Vasconcelos et al.'s method; they are always same during the retrieval process. Another difference is that two consecutive feedbacks are dependent in RGR, but in the two above-mentioned methods, they are assumed to be independent.

2. Bayesian relevance feedback

Relevance feedback can be considered as a Bayesian classification problem. Based on user's feedback, the positive examples and negative examples can be treated as two classes. The first is Ω^+ that represents the set of images the user specified as the positive examples. The second is Ω^- that indicates the set of negative examples. We define two priori probabilities ($p(\Omega^+)$ and $p(\Omega^-)$) for the Ω^+ class and the Ω^- class. And then, the class-conditional probability density function (PDF) for Ω^+ is written as $p(x|\Omega^+)$. Therefore, the two PDFs can be computed from the statistic of the Ω^+ and Ω^- that user specified. Under the Bayesian rule, the posterior probabilities of an image x in the database can be calculated as

$$p(\Omega^+|x) = \frac{p(x|\Omega^+)p(\Omega^+)}{p(x|\Omega^+)p(\Omega^+) + p(x|\Omega^-)p(\Omega^-)} \tag{1}$$

and

$$p(\Omega^-|x) = 1 - p(\Omega^+|x). \tag{2}$$

It is worth mentioning that $p(\Omega^\pm|x)$ should be calculated in each feedback step. This is because the user may give variant feedback every time. After each feedback, all images in the database are ranked according to $p(\Omega^+|x)$ in a descendent order. Under the optimal condition, the images that are similar to positive examples will have high $p(\Omega^+|x)$, whereas the images that are similar to negative examples will have low $p(\Omega^+|x)$. In fact, the user may not provide sufficient feedback examples in one interaction; therefore the feedback will be repeated until finding the most relevant images. To represent the interaction process, we introduce the variable t to indicate the feedback time. Given the time t, $p(\Omega^\pm(t))$, $p(x|\Omega^\pm(t))$ and $p(\Omega^\pm(t)|x)$ represent the prior probabilities, class-conditional PDFs and posterior probabilities respectively. Now $\Omega^+(t)$ is the cumulated image set from the interaction 1 to t. Eqs. (1) and (2) is rewritten as

$$p(\Omega^+(t)|x) = \frac{p(x|\Omega^+(t))p(\Omega^+(t))}{p(x|\Omega^+(t))p(\Omega^+(t)) + p(x|\Omega^-(t))p(\Omega^-(t))} \tag{3}$$

and

$$p(\Omega^-(t)|x) = 1 - p(\Omega^+(t)|x). \tag{4}$$

To employ the user feedback history, $p(\Omega^\pm(t)|x)$ can be computed from the statistic of all feedback examples. Different statistic strategies will lead to different relevant feedback solutions.

3. RGR

In this section, RGR is described in detail. RGR keeps the relevant images with higher and higher updated relevance probabilities and propagates user's feedback information into the retrieval process step by step. As a result, the images that