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Ego-similarity measurement for relevance feedback

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ABSTRACT

Relevance Feedback in Content-Based Image Retrieval is an active field of research. Many mechanisms of Relevance Feedback exist with many interactive techniques and implement criteria. In this paper, we proposed a novel approach of RF which can set adaptive weights of similarity measurement for each database image from the user feedback, i.e. ego-similarity measurement. We would explore the feedback records were archived in the two different ways that stored along with query images (QRF-based) or along with each retrieved relevant image from the image database (DBRF-based). In the experiment, DBRF-based relevant feedback improved greatly in the retrieval effectiveness.

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1. Introduction

Through the development of the multimedia devices such as image creation, storage and transmission that are easy in application, thousands of the digital information is produced speedily. Besides, with the development of the World Wide Web, not only the transmissions of the images become easier but also the image database needs the requirement of large storage capacity. Therefore, the image-based searches require the effective and efficient digital index and retrieve relevant images from the large image database after user gives the query image on the internet.

Content-based image retrieval (CBIR) is one of the techniques for image retrieval. In the CBIR context, images are represented by a set of multidimensional low-level visual features like color, shape, spatial, texture, etc. And the system can extract the features of the images and retrieve the relevant images from the image database automatically has gotten more attention. In the past years, the CBIR is a popular research topic in the image and vision computing. The CBIR systems had been developed in terms of multi-approaches such as BALAS (Zhang & Zhang, 2006), MIRROR (Wong, Cheung, & Po, 2005), Netra (Ma & Manjunath, 1999), Photobook (Pentland, Picard, & Scaroff, 1996), PicHunter (Cox, Miller, Minka, Papathoman, & Yianilos, 2000), PicSOM (Laaksonen, Koskela, Laakso, & Oja, 2001), QBIC (Flickner et al., 1995), SIMPLIcity (Wang, Li, & Wiederhold, 2001), Virage (Gupta & Jain, 1997), VisualSeek (Smith & Chang, 1997) and so on (Huang & Lee, 2004; Liu, Zhang, Lu, & Ma, 2007; Subramanyam Rallabandi & Sett, 2008).

More recently, how to improve the retrieval results of CBIR has been an interesting issue. Relevance feedback (RF) is one of the mechanisms of increasing the accuracy of the retrievals and can be integrated in the retrieval process. The most researches of the RF discuss the algorithms and manipulations of the proposed schemes and compare the retrieval results with the different RF approaches.

In this paper, we proposed a novel RF approach whose feedback records will archive in the different ways. Our approach will adjust the similarity measure based on the importance for each feature. And the retrieval system is able to adapt the search results to user's query preference. This mechanism greatly reduces the labor requirement to precisely compose a query and easily capture the user's subjective preference of the retrievals (Lee & Lin, 2008). Therefore, it can attain a system's objective and user's subjective balance. However, each image has its own important features. Each image has its own feature weights in similarity measurement will achieve a more precisely retrieval. Rather than previous research, most system designs a similarity measurement for a whole image database. Though the feedback procedure, we can capture the characteristic of each image to formulate proper ego-similarity measurement for itself.

The remainder of this paper is organized as follows. In Section 2 discusses the related works of the RF. The details of the RF mechanism and ego-similarity measurement are described in Section 3. Section 4 introduces the experiment of our proposed RF approach. Finally, Section 5 summarizes the conclusions of the paper.

2. Related works

Relevance feedback is an automatic technique originally proposed for traditional text-based information retrieval systems to

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increase the accuracy of the documents retrieved. Nowadays, there are more interactive RF techniques able to improve the performance in the procedure of the Content-based image retrieval (Wang, Zhang, & Li, 2006). The RF mechanism is an iterative learning process, which is generally treated as online supervised learning (Huang, Zhou, Nakazato, Wu, & Cohen, 2002). Many researches indicate that the self proposed RF method for the CBIR can improve the precision of the retrieval. Through the RF mechanism, the precision of the retrieved results of the image database can be improved in the CBIR (Saha, Das, & Chanda, 2007). Consequently, RF is a popular approach which has emerged from CBIR.

A typical scenario for RF in CBIR is shown as below (Yin & Li, 2006): First, the user inputs a query image to system which is carried on comparing the similarity of the query image with the images in the database and presents the retrieval result. Whether the image is irrelevant or relevant to the query image, it is based on personally subjective judgment. System uses related information to update the reformulated query vector, feature weights and prior-possibilities of relevance through the RF process, which helps next query results being nearer the user's requirement. The process is repeated until the user is satisfied or the results cannot be further improved. Fig. 1 shows a simple diagram of a CBIR system with RF.

In the recent years, the RF researches have been investigated multi-aspects. The main goal is to improve the performance of the retrievals. There are roughly three types of the typical RF techniques as below (Doulamis & Doulamis, 2006; Grigorova, De Natale, Dagli, & Huang, 2007; Liu et al., 2007; Yin & Li, 2006): (1) Query Point Movement (QPM) improves the query image representation through the user's feedback. The Rocchio's formula (Chen & Zhu, 2002) has been often used to move it towards the relevant images and away from the irrelevant images. Furthermore, QPM has two main aspects including the single point query movement and the multiple point query movement. (2) Re-Weight adjusts the weights of each image feature of the similarity measure from the user's feedback based on Euclidean distance such as weighted Euclidean distance and generalized Euclidean distance. This approach assumes not only the image has composed by the different features, but also each feature has the particular weight in the similarity measure. (3) Machine Learning Techniques have been used in many researches of the RF like Bayesian, C4.5, ID3, Fuzzy, SOM, SVM, and so forth. Through the learning mechanism, they supervise the operating process of the user in the CBIR to analyze automatically and improve retrieval performance.

More recently, the most researches of the RF emphasize that the weights of similarity measurement are adjusted by the user's feedback (Liu et al., 2007). Because each image contains multi-features and in order to increase the retrieval performance, the features must be combined the features in the similarity measure. Through the RF mechanism, each feature can automatically refine its own weight (Yoo, Jang, Jung, Park, & Song, 2002). The general researches of the re-weight RF techniques consider to update a common similarity measurement and determine the weights of each feature by the whole retrieved relevant images (Irwin & Zhong, 2003; Kherfi & Ziou, 2006; Tai, Wu, Ren, & Kita, 2006; Yoo, 2008; Yoo et al., 2002, Yoo, Park, & Jang, 2005). However, each image has oneself specific important low-level features. The similarity measure could reflect characteristic of each image will achieve a more precisely retrieval. In this paper, the main idea is each image has ego-similarity measurement which can be acquired by two ways. One is RF mechanism archived in the query images (QRF-based) or in each retrieved relevant image from the image database (DBRF-based).

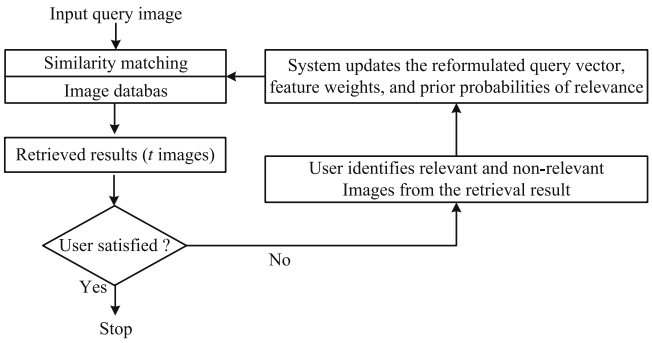

Fig. 1. CBIR system with RF (Yin & Li, 2006).

3. Relevance feedback

In this section, the first subsection describes the similarity measurement. The second subsection provides details on the formulation of our RF approach and how to set adaptive weights of similarity measurement from user's feedback. Finally, the third subsection shows a relevance feedback algorithm using ego-similarity measurement.

3.1. Similarity measurement

The performance of the CBIR system depends on the particular image representation and similarity measurement. In many applications of the CBIR, combined low-level features are used for the excellent performance. In this subsection, we will introduce some common features in the image database. A database is denoted by X. There are totally N images in the database, that is $X = \{x_1, \ldots, x_N\}$. The query image is represented by q. The $T(q)$ means image representing features.

Image similarity measures the distance between two images based on low-level features in CBIR systems. In order to increase the accuracy of the retrievals, similarity measurement should contain multiple features. The feature similarity function is defined as Eq. (1)

$$\begin{aligned} Sim(T(q),T(x)) = {} & W_1 Sim_1(T(q),T(x)) + W_2 Sim_2(T(q),T(x)) \\ & + \cdots + W_k Sim_k(T(q),T(x)) + \cdots \\ & + W_i Sim_i(T(q),T(x)) \end{aligned} \quad (1)$$

There are i types of features in the formula. In the initial step, the value of W_k is the weight for feature k set to $\frac{1}{i}$ initially, where $k = 1, 2, \ldots, i$.

3.2. Relevance feedback mechanism

We proposed the weight for each feature in similarity measure is not equal. We will show how to choose the adaptive weight for each feature in this subsection. In addition, we observed that two images are similar if they are jointly labeled as relevant to the same query in a RF phase. Rui, Huang, Ortega, and Mehrotra (1998) suggested a RF approach that has five RF levels such as highly relevant, relevant, no opinion, irrelevant and highly irrelevant, each level is assigned to an value.

A search session starts with a query image phase and is possibly followed by one or more RF phases. The basic idea of the approach is tuning the similarity measurement by the RF from the user. There are totally five values for the user's subjective judgment and we add an elasticity parameter α in this paper. Therefore, the user can start a query process that the similarity degrees between query image and the database image are assigned initially. The system automatically refines similarity measurement that uses relevant feedback information to fit user's recognition.

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