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Interpretation of users' feedback via swarmed particles for content-based image retrieval

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A B S T R A C T

While providing relevance feedback (RF) by users proves to be an effective method for content-based image retrieval, how to interpret and learn from the user-provided feedback, however, remains an unsolved problem. In this paper, we propose an integrated users-feedback and learning algorithm by screening individual elements of content features and driving a group of swarmed particles inside the feature space to provide a possible solution. In comparison with the existing approaches, the proposed algorithm achieves a number of advantages, which can be highlighted as: (i) interpretation of users' feedback is independent of both the content features and relevance feedback schemes, and hence the proposed algorithm can be applicable to any content features and relevance feedback methods; (ii) the RF interpretation is followed by a group of swarmed particles, acting as multiple agents rather than a single query image in searching for the desirable images; (iii) the proposed RF interpretation and learning is exploited not only in reweighting the content similarity measurement, but also in regrouping the database images. Extensive experiments support that our proposed algorithm outperforms the existing representative techniques, providing good potential for further research and development for a wide range of content-based image retrieval applications.

1. Introduction

Relevance feedback (RF) is a semi-automatic strategy which collects information from users and then exploits the information by either re-weighting the content similarity measurement or revising the query [1–3]. For the former, the RF information is used to modify the solution space metrics, i.e., the weights of feature-based distances are redefined according to the knowledge learned from RF [1–5]. For the latter, which is also known as query refinement [6–10], the original query will move towards the center of the relevant image clusters and thus an optimized query strategy is produced to direct the next iteration of image retrieval and users feedback [7,11–16].

Typical relevance feedback for content-based image retrieval (CBIR) systems require users to input an image as the query, and the nearest images are retrieved and returned according to certain criteria for users to provide relevance feedback [17,18]. To measure the closeness between the query and all other images inside the database, every image is mapped into

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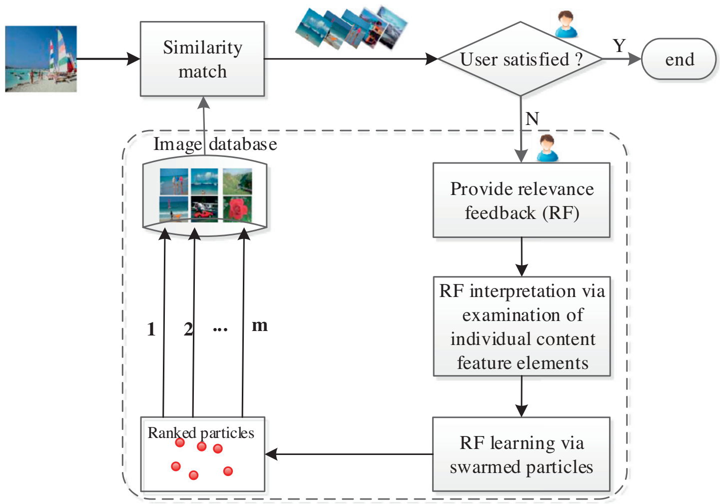

Fig. 1. Overview of the proposed algorithm.

a content feature vector space through feature extraction techniques [19–21], and a variety of weighted distance measurements is often calculated to complete the similarity measurement [3,7,9,10,22,23].

Over the past decades, RF has been successfully used in a range of content-based image retrieval (CBIR) applications and widely researched within the information technology, data engineering, and multimedia communities. For example, RF was modeled as a SVM-based classifier by Djordjevic et al.[4], and a graph-based model by Kundu et al.[8]. Research reported over recent years focused on combinational modeling with text-based queries [4,8,24,25], which are used to explore the world of semantics and knowledge in organizing relevance feedback and re-ranking retrieval results as well as different elements of the queries.While majority of the existing research is limited to feature-based relevance feedback, including Bayesian framework[26], perceptual feature modeling [27,28], instance-based relevance feedback[29], attribute-based relevance feedback[16], and wavelet-based clustering[30] etc., a thorough survey on the existing RF techniques for image retrieval is introduced in [31,32], and several RF methods and schemes are evaluated and compared in [33] and [27].

While introduction of relevance feedback successfully decomposes the content-based image search into several consecutive retrieval sessions and let users to provide feedback in improving its effectiveness, how to reduce the number of iterations to achieve efficient convergence remains a challenging problem[34]. This is particularly difficult when only a few new images (possibly none) are retrieved during the early stages of the relevance feedback sessions. Cho et al.[6] combined RF with an interactive genetic algorithm (IGA), which is employed to help the users to identify the images that are most satisfied to the users needs. Arevalillo-Herráez et al.[35] proposed a multiple similarity measurement scheme to establish the RF model, and Qi et al.[36] combined shape description in the process of feature match for effective retrieval of trademark images. In [29], Gia et al. developed an instance-based RF scheme, in which feedback scores are computed for each retrieved image as a function of both the distance to the nearest non-relevant image and the distance to the nearest relevant image. Following the introduction of a so-called particle swarm optimization (PSO)[37] by Parsopoulos and Vrahatis, Broilo et al. applied the scheme to optimize the relevance feedback and reported improved retrieval results [34,38].

To forward the existing research efforts, we feel that one of the essential research problems for RF-based image search is how to learn and interpret the users feedback to improve the content-based image retrieval performances. The difficulty, however, lies in the fact that all RF algorithms reported in the literature have different schemes by nature and it remains challenging to develop a universal interpretation scheme to achieve the once-for-all effect. To this end, we formulate a general RF-based image retrieval framework, where only those common principles are taken into consideration, which can be highlighted as: (i) to measure the content similarity between the query image and images inside the database, content descriptors are often required, and all of them can be generally represented as an integrated vector; (ii) no matter how different the relevance feedback is designed, the eventually returned images by users can always be qualified as either relevant or irrelevant. Even for those recently developed interactive RF schemes[16], where users' interaction is presented by text-based statements, our proposed RF interpretation based on relevant and irrelevant can still work. For example, in the relevance feedback developed by Kovashka et al.[16], every interaction before the text statement is added can be classified into the two sets, relevant and irrelevant. In this way, a platform for analyzing individual element of the content features or descriptors can be formulated and corresponding knowledge can be discovered to drive the learning from both the relevant and irrelevant images, and hence complete the interpretation of relevance feedback towards improvement of content-based image retrieval. Fig. 1 illustrates an overview of our proposed RF interpretation algorithm in reflection of our proposed strategy as given above.