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Multi-Query Parallel Field Ranking for image retrieval

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ABSTRACT

Relevance feedback image retrieval is an effective scheme bridging the gap between low-level features and high-level concepts. It is essentially a multi-query ranking problem where the user submitted image and provided positive examples are considered as queries. Most of the existing approaches either merge the multiple queries into a single query or consider them independently, and then the geodesic distances on the image manifold are used to measure the similarities between the query image and the other images in database. In this paper, we propose a novel approach called Multi-Query Parallel Field Ranking (**MQPFR**) which finds an optimal ranking function whose gradient field is as parallel as possible. In this way, the obtained ranking function varies linearly along the geodesics of the data manifold, and achieves the highest value at the multiple queries simultaneously. Extensive experiments are carried out on a large image database and demonstrate the effectiveness of the proposed approach.

1. Introduction

Content-Based Image Retrieval (CBIR) has received considerable interest recently [1], partly because of the rapid growth of the mobile devices. Unlike traditional keyword based search systems, CBIR utilizes the low-level visual features automatically extracted from images, including global features (e.g. color moment, edge histogram, LBP) and local features (e.g. SIFT). How to narrow down the semantic gap between low-level features and high-level concepts is a challenging problem.

To bridge the semantic gap, relevance feedback is introduced into CBIR to capture the subjectivity of human perception of images through interactions with the user [2]. It was shown to dramatically increase the retrieval performance. Most of previous relevance feedback methods can be classified into two categories according to the way they deal with the user submitted query, as well as the user provided positive examples. The first merges multiple queries into a single one and considers image retrieval as a ranking problem [3]. The other considers the problem as classification [4,5]. However, sometimes the users only provide positive examples, in which case classification algorithms cannot be directly applied due to the lack of negative examples. In this work, we consider relevance feedback image retrieval as a multi-query ranking problem and aims to learn a ranking function whose highest values are achieved at the multiple queries simultaneously.

Many manifold-based ranking approaches have been proposed [6–11], following the intuition that naturally occurring data (e.g. images) may be generated by structured systems with possibly much fewer degrees of freedom than the ambient dimension would suggest [12,13]. These approaches usually estimate the data manifold by an affinity graph, and the Laplacian regularizer constructed over the graph is thus adopted to ensure the smoothness of the learned ranking function along the geodesics of the data manifold. It has been shown that manifold-based approaches have significantly improved image retrieval performance. However, one of the major limitations is that Laplacian regularization can only ensure smoothness, while an optimal ranking function should preserve the ranking order of the data points along the geodesics. In other words, the ranking function should vary monotonically along the geodesics on the data manifold.

In this paper, we propose a novel algorithm, called Multi-Query Parallel Field Ranking (**MQPFR**), for learning an optimal ranking function on the data manifold which varies linearly along the geodesics and achieves the highest ranking score at the multiple queries. In order to find such a function, we note that recent theoretical works show that its gradient field has to be a parallel vector field [14,15]. Thus, we adopt the same idea to learn a ranking function f and a vector field V simultaneously such that ∇f is as close to V as possible and ∇V vanishes. Moreover, the user submitted query and the provided positive examples are equally treated as multiple queries by requiring that, for each one of them, the tangent vectors of its nearest neighbors should all point to it. In this way, our proposed approach effectively makes use of the multiple queries and the intrinsic distribution of data.

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2. Related work

Image retrieval has been researched intensively, with a large number of content-based ranking methods proposed every year. While earlier image retrieval algorithms rank data directly according to the Euclidean distance of simple image features like color features [16], more recently proposed algorithms like [17] learn a parameterized similarity function among all data based on pairwise similarity. In order to exploit the intrinsic distribution of all data, Zhou et al. proposed a transductive ranking algorithm called Manifold Ranking (MR) by diffusing the label information among data neighborhoods via a heat equation [6]. It is significantly different from distance-based ranking algorithms which only consider pairwise distances or inner products as shown in [18,7]. Recently, more algorithms that directly make use of the data manifold assumption [12,13] and address specific issues of the original MR have been proposed. For example, He et al. [10] and Yu and Tian [11] solve for linear or nonlinear projections of the original image features before comparing the Euclidean distance among data. The LRGA algorithm proposed in [8] learns the Laplacian matrix for ranking data using local linear regression rather than directly computing it using the Gaussian kernel. Yang et al. [9] addressed multi-modality retrieval tasks by harmonizing hierarchical data manifolds, and thus applied in scenarios like multi-task and cross-media retrieval. Still in other frameworks, extra label information can be incorporated as explicit constraints into the projection process [19] and more powerful and robust techniques such as the iterated graph Laplacian [20], k-regular nearest neighbor graph [21], anchor graph [22] and parallel vector field [15] are adopted for better performance and scalability of ranking on data manifolds. Compared with inductive learning algorithms, those frameworks can make use of both unlabeled and labeled data for ranking and thus yield more stable and accurate ranking results.

Relevance feedback has been shown helpful in many image retrieval systems [2–5,7,9–11,23,24]. Short-term relevance feedback algorithms that only consider feedback information provided by the current user are usually derived directly from some manifold-based ranking algorithms with carefully constructed queries [7,9], or from classification algorithms with ranking scores computed from the decision values [4,5]. To make use of the feedback information provided by more users, various long-term relevance feedback algorithms have also been proposed [23,9,10]. Moreover, other algorithms like [25,26] apply active learning to achieve better understanding of user preferences at the cost of less flexible interactive processes.

Our algorithm addresses short-term relevance feedback image retrieval as a multi-query ranking problem and exploits the intrinsic distribution of whole data to improve ranking results, which is generally similar to MR and LRGA [7,9]. But unlike them, we employ the parallel vector field to ensure the linearity of our ranking function and we adopt the anchor graph to speed up the optimization processes.

3. Multi-Query Parallel Field Ranking

In this section, we begin with the motivation of our algorithm and then introduce the objective function which learns a multi-query ranking function on the data manifold.

3.1. From single query to multiple queries

The generic problem of image retrieval can be described as follows. Given an image database $\{x_i\}_{i=1}^{n} \subset \mathbb{R}^m$ and an initial query image $q_1 \in \mathbb{R}^m$, learn a ranking function f such that $f(x_i)$ reflects the semantic relationship between x_i and q_1. However, in many real applications, only one query is not enough to convey useful information and relevance feedback is an effective way of enhancing the learning process. The typical relevance feedback based retrieval process can be outlined as follows:

1. The system presents the top ranked images to the user by using a pre-defined ranking function f, such as Euclidean distance function.

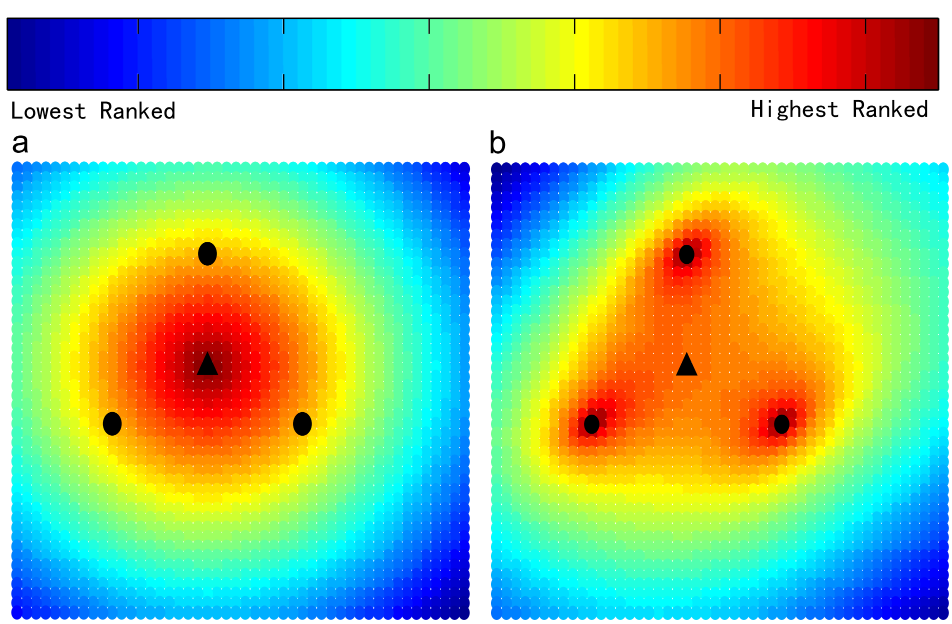

Fig. 1. A toy example illustrating the ranking results with single query and multiple queries. In this example, three query points (marked by '•') in a two-dimensional space are given. The color represents the ranking score from the highest (red) to the lowest (blue). (a) Ranking result obtained by the Parallel Field Ranking algorithm. The three queries are merged into a single query, which is marked by '▴'. As it can be seen, the ranking function fails to achieve the highest score at the three queries which represent user needs. (b) Ranking result obtained by our approach. We can see that the highest ranking score is achieved at the three queries simultaneously. (a) Rank by merging three queries into a single one and (b) rank with three queries simultaneously. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this paper.)