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Video Search Reranking using Multimodel fusion Technique

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***Abstract*- Analyzing click-through data from a huge search engine log information shows that users are usually interested in the top-ranked portion of returned search results. So, it is crucial for search engines to achieve high accuracy on the top-ranked documents. While many methods exist for enhancing video search performance, they either pay less attention to the above factor or encounter difficulties in practical applications. In this thesis, we present an easy and quality reranking method, called CR-Reranking, to increase the retrieval effectiveness. To offer high accuracy on the top-ranked results, CR-Reranking employs a cross-reference(CR) strategy to fuse multimodal cues. Specifically, multimodal features are first utilized separately to rerank the initial returned results at the cluster level, and then all the ranked clusters from different modalities are cooperatively used to infer the shots with high relevance. After the fusion process the results shows that the search quality, especially on the top-ranked results, is improved significantly.**

Keywords – ***CR-Reranking, cross-reference (CR), multimodal.***

1. INTRODUCTION

Recent advances in communication, and data storage have led to an increasing number of large digital libraries publicly available on the Internet. In addition to alphanumeric data, other modalities, including video play an important role in these libraries. Ordinary techniques will not retrieve required information from the enormous mass of data stored in digital video libraries.

Instead of words, a video retrieval system deals with collections of video records. Therefore, the system is confronted with the problem of video understanding. The system gathers key information from a video in order to allow users to query semantics instead of raw video data or video features. Users expect tools that automatically understand and manipulate the video content in the same structured way as a traditional database manages numeric and textual data. Consequently, content-based search and retrieval of video data becomes a challenging and important problem. As an emerging research field, content-based video retrieval (CBVR) has attracted a great deal of attention in recent years. While various retrieval models have been developed to improve video search quality, most of them implement search procedure by implicitly or explicitly measuring the similarity between the query and database shots in some low-level feature spaces .However, such Similarity is not usually consistent with human perception due to the limitation of current image/video understanding techniques.

That is, the semantic gap exists between the low-level features and high-level semantics. For example, although a scene with red flags and a scene with red buildings share similar color features, they have completely different semantic meanings. The semantic gap will enlarge linearly with the increase of data set size since a larger data set means more confusion, which thereby leads to rapid deterioration of search performance. Performance comparison between TRECVID’05 and TRECVID’06 evaluation on all the three search types, i.e., automatic, manual, and interactive, also reveals it. Consequently, it is more attainable for low-level features to reliably distinguish different shots in a relatively small collection, which is the basis of proposed reranking scheme.

If we consider that the final aim of search engines is to meet users’ information needs, it is reasonable to take user satisfaction and user behavior into account when designing a search engine. According to the analysis in, users are rarely patient to go through the entire result list. Instead, they usually check the top-ranked documents. Analysis on click-through data from a very large Web search engine log also reflects such preference. Therefore, it is more crucial to offer high accuracy on the top-ranked documents than to improve the whole search performance on the entire result list.

The Meta search strategy, which is originally put forward in the field of information retrieval, is imported to CBVR for improving video retrieval effectiveness.The key idea of Meta search

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is that multiple result lists returned by several different search engines in response to a given query are aggregated into a single list in an optimal way. Meta search is generally based on the "unequal overlap property": different searchmodels retrieve many of the same relevant documents, using this property; the combination of the returned lists is performed by simply Giving higher ranks to the documents that are contained simultaneously in multiple result lists.

2. EXISTING SYSTEM

Top ranked portion of returned results only available not like queried output as like text search. Different search engines for both text and video search will populates different contribution of search queries. i.e., output will be different on the text as well as video querying. Users are rarely patient to go through the entire result. Instead, they usually check the top-ranked documents. Analysis on click-through data from a very large Web search engine log also reflects such preference. Therefore, it is more crucial to offer high accuracy on the top-ranked documents than to improve the whole search performance on the entire result list. Sometimes it is time consuming and impractical search scenarios.

3. PROPOSED SYSTEM

Results are first clustered into three clusters, and then the resulting clusters are mapped to three predefined rank levels, i.e., High, Median, and Low.

The reranking method can improve search quality by reordering the initial result list. Although the total number of relevant documents remains fixed after reranking, the precision improvement at the low depth of the result list can be expected by forcing true relevant documents to move forward.It finds some relevance-consistent clusters first and then ranks shots within the resulting Clusters. In this

The framework of CR-Reranking is illustrated in Figure, where d1; d2; . . . ; d8g denotes the initial result list ranked according to text-based search scores. The initial result list is processed individually in two distinct feature spaces, i.e., feature spaces A and B. In each feature space, all the results are first clustered into three clusters, and then the resulting clusters are mapped to three predefined rank levels, i.e., High, Median, and Low, in terms of their relevance to the query. Finally, a unique and improved shot ranking is formed by hierarchically combining all the ranked clusters from two different spaces. Note that only two modalities (or features) are considered here; however, the system can be method, however, multiple modalities are integrated in a unique feature space, that is, multimodal features are fused by concatenating them into a single representation. This fusion strategy is called early fusion.

4. SYSTEM ARCHITECTURE

The clusirintg and fusion technique is explained in the architeural blok dig shown in fig 1.

Clustering

The goal of clustering is to separate relevant documents from non-relevant documents. To accomplish this, we need to define a measure for the similarity between documents and design corresponding clustering algorithm.

Fusion

Which is the process or the result of joining two are more things togather to form single entity.Which is explained in fig.1.

5. PROPOSED ALGORITHM

A. Clustering algorithm

There are many clustering algorithms for document clustering. Our task is to cluster a small collection of documents returned by individual retrieval systems. Since the size of the collection is 1,000 in our experiments, the complexity of the clustering algorithm is not a serious problem.

1. Randomly set document d_i to cluster *Cj* ;
2. LoopCount =0; ShiftCount = 1000;
3. While (LoopCount < LoopThreshold and ShiftCount > ShiftThreshold) Do
4. Construct the centroid of each cluster, i.e.

$$\text{Centroid of } C_j = \frac{\sum_{d_i \in C_j} d_i}{|C_j|}$$

5. Assign d_i to its nearest cluster(the distance is determined by the similarity between d_i and the centroid of cluster);
6. ShiftCount = the number of documents shift to other cluster;
7. LoopCount++;

Our final goal is to obtain a unique and improved reranking of the initial results, especially paying more attention to the accuracy on the top-ranked shots. In order to move vigorously toward this goal, we hierarchically fuse all the ranked clusters from different modalities using a cross reference strategy. Fig1. illustrates the schematic diagram of our fusion method with three rank levels (i.e., High, Median, and Low).

As shown in Fig1 our fusion approach is composed of three main components: combining these ranked clusters using cross-reference strategy,

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ranking subsets with the same rank level, and ranking shots within

Rank(Ai ∩ Bj) > Rank(Am ∩ Bn);

if (i + j) = (m + n), hd(E,Ai ∩ Bj)<hd(E;Am ∩ Bn);

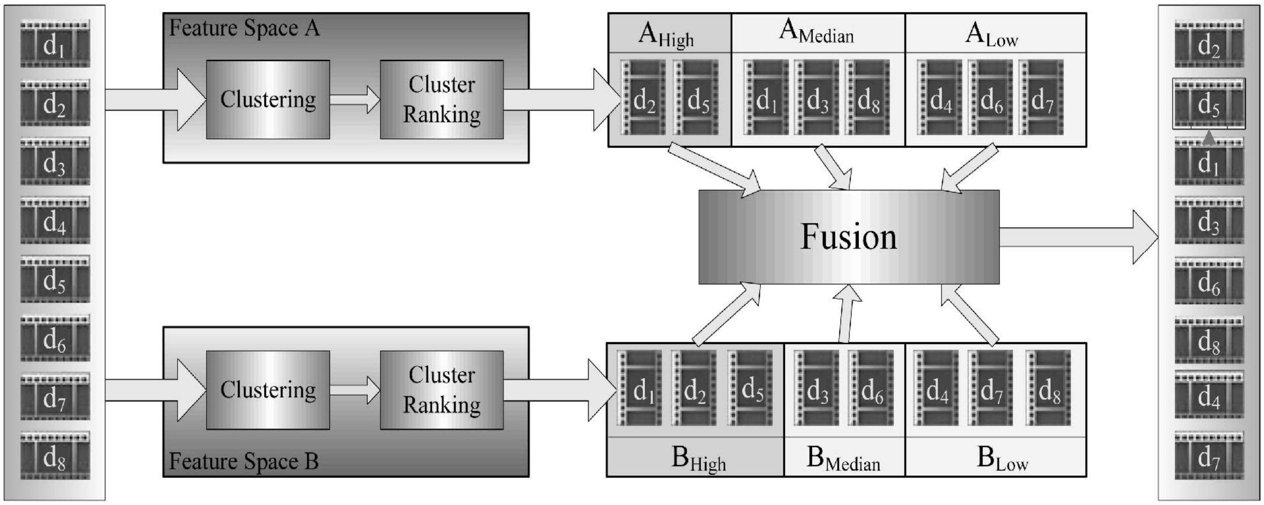

Fig.1. Block diagram for fusion method

the same subset. Note that the rank levels are denoted numerically in the following formulas for the convenience of expression. The rank levels High, Median, and Low in Fig are equivalent to the rank levels 1, 2, and 3, respectively.

We assume that a shot has a high rank if it exists simultaneously in multiple high-ranked clusters from different modalities. Based on this assumption, we put forward a cross-reference strategy to hierarchically combine all the ranked clusters, leading to a coarsely ranked subset list. Specifically, let fA1;A2; . . .;ANg and fB1;B2; . . .;BNg be the sets of the ranked clusters from feature spaces A and B, respectively, and Rank be the operation of measuring the rank level of a cluster or shot. The ranked clusters in each set are arranged from high-rank level to low-rank level in ascending order of their subscripts, that is, Rank(Ai) is greater than Rank(Aiþ1). Then, two ranked cluster sets can be integrated into a unique and coarsely ranked subset list

According to the following inference rule:

Rank(Ai ∩ Bj) > Rank(Am ∩ Bn)

If (i + j) < (m + n) i. j,m; n ¼ 1; . . .;N;

where N is the number of clusters, and Ai ∩ Bj stands for the intersection of clusters Ai and Bj.

As a matter of fact, the rank levels of subsets cannot be compared using merely the above criteria if (i + j) is equal to (m + n), just like the intersections (A1 ∩B2) and (A2 ∩ B1). To address this issue, we employ the method used in the cluster ranking step to order those subsets,

which can be formulized as follows:

where the distance hd(,) can be computed in any of the feature spaces.

6. FUTURE SCOPE

As analyzed previously, the proposed reranking method is sensitive to the number of clusters due to the limitation of cluster ranking. In the future, we will develop a new method to adaptively choose cluster number for different feature spaces. In addition, new strategies are to be investigated for selecting query-relevant shots, e.g., using pseudo negative samples to exclude irrelevant shots.

7. CONCLUSION

We present a new reranking method that combines multimodal features via a cross-reference strategy. It can handle the initial search results independently in various modality spaces. Specifically, the initial search results are first divided into several clusters individually in different feature spaces. Then, the clusters from each space are mapped to the predefined ranks according to their relevance to the query. Given the ranked clusters from all the feature spaces, the cross-reference strategy can hierarchically fuse them into a unique and improved result ranking. Experimental results show that the search effectiveness, especially on the top ranked results, is improved significantly.

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