Concept-Based Interactive Search System

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Abstract. Our successful multimedia event detection system at TRECVID 2015 showed its strength on handling complex concepts in a query. The system was based on a large number of pre-trained concept detectors for textual-to-visual relation. In this paper, we enhance the system by enabling human-in-the-loop. In order to facilitate a user to quickly find an information need, we incorporate concept screening, video reranking by highlighted concepts, relevance feedback and color sketch to refine a coarse retrieval result. The aim is to eventually come up with a system suitable for both Ad-hoc Video Search and Known-Item Search. In addition, as the increasing awareness of difficulty in distinguishing shots of very similar scenes, we also explore the automatic story annotation along the timeline of a video, so that a user can quickly grasp the story happened in the context of a target shot and reject shots with incorrect context. With the story annotation, a user can refine the search result as well by simply adding a few keywords in a special "context field" of a query.

Keywords: Video search · Known-Item Search · Concept bank · Semantic query · Video reranking · Story annotation

1 Introduction

In TRECVID 2015, we developed a multimedia event detection system for zero-example event detection that achieved the best performance [4]. The core of the system is a large concept bank that contains about 2,800 pre-trained concept detectors covering common objects, actions, scenes and everyday activities. To perform a text query search in an unannotated video corpus, the crux of the system is to solve the textual-to-visual relation using the concept bank as a knowledge base.

We have studied several facts which significantly impact retrieval performance. Such facts include the number of concepts, concept specificity, and concept discriminativeness regarding the query. However, the performance of an automatic video retrieval system is still far from perfection, especially when no precisely matched concepts can be found in the concept bank. In this case, the system would propose concepts with the smallest word distance towards the query. This metric, however, often suggests off-topic concepts due to a lack of

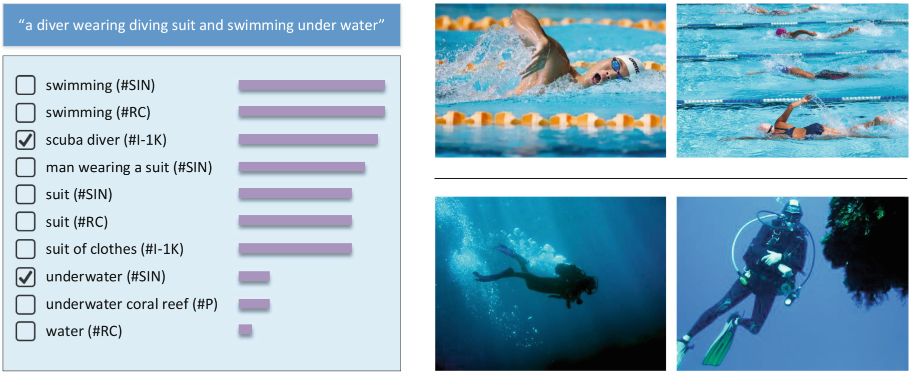
L. Amsaleg et al. (Eds.): MMM 2017, Part II, LNCS 10133, pp. 463–468, 2017.
DOI: 10.1007/978-3-319-51814-5_42

common sense that can distinguish a concept from the context of the query topic. A feasible solution is to employ a human evaluator to quickly adjust the result by screening the machine-proposed concepts. On the other hand, although our existing system can be adapted to Ad-hoc Video Search, it is inefficient for Known-Item Search. This is because a text query is insufficient to describe the fine details which are required to mine the exact query clip from a number of clips sharing the same semantic content. Hence, a human needs to painstakingly dig into hundreds of results to find the correct match even if the top results are all relevant. We, therefore, seek help from an interactive search where a user can refine a first-time search result with different methods so that the correct match has a higher chance to show up.

Video Browser Showcases [8] in previous years suggest using high-level visual concepts [5–7] and low-level visual descriptors [1,2] as two lines of approach. For Known-Item Search, the systems using low-level features generally have an advantage over those using high-level concepts. It is worth to mention that a color sketch search method was shown to be very effective in 2014 and 2015 [1,3]. But as low-level features do not contain semantic information, the systems with high-level concepts have their inherent benefit on Ad-hoc Video Search where queries are only formed by text. In this paper, we tend to integrate both methods into an interactive search system. The concept-based search system is mainly used for generating the first-time search result. Then, we implement different reranking techniques to incorporate the strength of both high-level concepts and low-level features. Specifically, highlighted concept reranking is a simple and quick method for a user to emphasize a particular characteristic in the query. When a user finds one or more visually relevant clips in the search result, either relevance feedback or color sketch can be further exploited to refine the result so that the user has a better chance to hit the correct answer. Furthermore, there is an increasing awareness of difficulty in distinguishing shots sharing very similar scenes in the search result [1]. We recount the dominant concepts along the timeline of a video to facilitate video browsing so that a user can quickly grasp the context of a target shot even though the shot itself is not distinctive. We also implement a *context field* in the query to quickly refine the result in this scenario. The following sections detail each component of our system.

2 Concept-Based Video Search System

We adapt our zero-example event search system to general-purpose video search. The search system is backed by a large concept bank which contains thousands of concept detectors for textual-to-visual relation. The most important module in our system is called *semantic query generation* which generates the internal query representation by calculating the distance from a query to each concept. The internal query, a.k.a. the *semantic query* is formed by a number of selected concepts with their weights. The weight calculation and concept selection are discussed in our paper [4].



"a diver wearing diving suit and swimming under water"

☐ swimming (#SIN)
☐ swimming (#RC)
☑ scuba diver (#I-1K)
☐ man wearing a suit (#SIN)
☐ suit (#SIN)
☐ suit (#RC)
☐ suit of clothes (#I-1K)
☑ underwater (#SIN)
☐ underwater coral reef (#P)
☐ water (#RC)

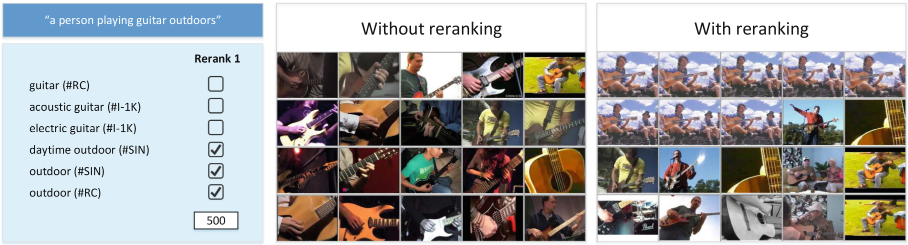
Fig. 1. (a) An example of semantic query editing. (b) Training examples for the concept "swimming" vs. the meaning of the term *swimming* under the context of the query.

As the queries in Ad-hoc Video Search are generally more specific and shorter, the term weights based only on the query are unreliable compared to the prolonged event query used in multimedia event detection. We, therefore, shed more light on semantic query editing by involving human-in-the-loop. As illustrated in Fig. 1a, given a text query *"a diver wearing a diving suit and swimming under water"* without any further editing, the system first generates a list of candidate concepts[1] loosely relevant to the query. The weight of each concept is indicated by a weight bar. A user then can quickly refine the concept list by removing wrong and non-discriminative [4] concepts, and watch the search result change at the same time. Figure 1b shows a typical wrong concept "swimming" which is easily identified by a human but difficult by a machine algorithm. As in a human's sense, the term *swimming* under the context of the query means *underwater diving* which is visually different from the sport *swimming* the concept automatically proposed. Furthermore, we also allow a user to adjust a concept's weight in order to strengthen or weaken the concept. For example, the concept "person" is not important in most query examples because the term is too common. While in some rare cases, such as *"a person sitting beside a laptop,"* the concept "person" should not be depreciated. A user thus can manually increase the weight for "person."

3 Video Reranking

In order to facilitate Known-Item Search, we implement three methods for video reranking. A user can adjust the scope of a reranking method. By default, a reranking is only performed within the top videos recommended by the concept-based video search. For example, *highlighted concept reranking* is most effective

[1] The tag in the brackets of Fig. 1a denotes the dataset from which the concept comes.



"a person playing guitar outdoors"

Rerank 1

- guitar (#RC) □
- acoustic guitar (#I-1K) □
- electric guitar (#I-1K) □
- daytime outdoor (#SIN) ☑
- outdoor (#SIN) ☑
- outdoor (#RC) ☑

500

Without reranking

With reranking

Fig. 2. (a) Concept reranking by emphasizing concepts about "outdoor". (b) The top results change accordingly.

in the scope of the top 300–500 videos. This limitation ensures that the algorithm is not applied to the semantically irrelevant videos at the bottom of the rank list.

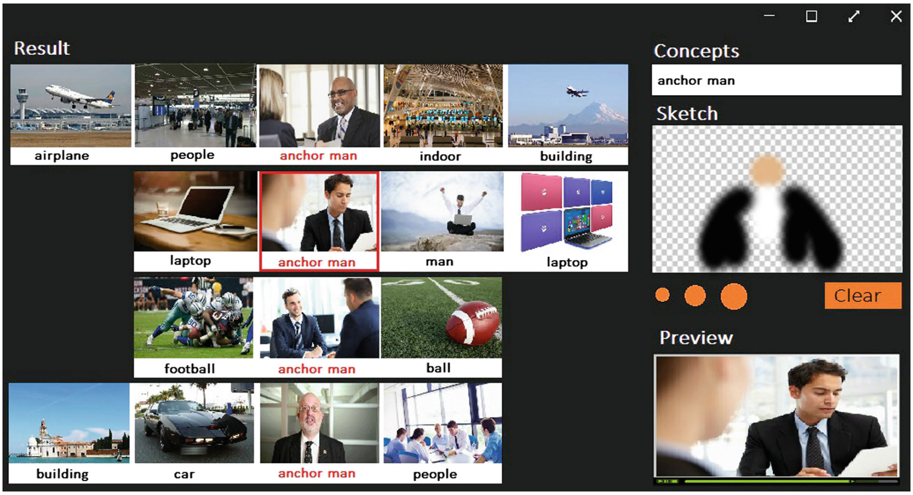
Highlighted concept reranking is a simple and quick reranking approach used to highlight particular characteristics in a semantic query. Figure 2a emphasizes the concept "outdoor" in the query *"a person playing guitar outdoors."* As shown in Fig. 2b, the top retrieval result of the original semantic query mixes guitar playing both indoors and outdoors. It is reasonable to highlight the concept "outdoor." But, if we simply increase the weight of "outdoor" in the semantic query, it would pull up noisy outdoor activities which do not contain guitar playing at all. A feasible way is thus to rerank only within the clips about guitar playing. Figure 2b shows the reranking result in the scope of the top-500 clips.

Relevance feedback is used when a user identifies one or more visually relevant clips. Even with highlighted concept reranking, the retrieval result is still diverse if the search system is only based on the high-level semantic concepts. Once a user has identified some relevant clips, these clips can be served as training examples having fine-grained visual details. We intuitively want to refine the result using these visual details. We train SVM classifiers for the user picked clips and rerank the result according to this feedback. The new result is expected to be much more specific and focused on the visually similar clips according to the user's choice.

Color sketch was a very successful approach in Video Browser Showcase 2014 and 2015 [1,3]. Basically, color sketch uses position-color features. These low-level features characterize the colors with their positions on a keyframe. A user can perform the search by simply drawing a few color circles on the empty canvas. We incorporate this search approach to be a reranking alternative mainly for its accuracy on Known-Item Search. In our system, the user can not only draw a new sketch but also use the color sketch automatically extracted from several marked clips in the search result for reranking.

4 Context Annotation

Video Browser Showcase 2014 raised a critical problem in Known-Item Search that it was difficult to distinguish the shots with very similar scenes in a search



Concepts: anchor man

Fig. 3. The context view for a search result. (Color figure online)

result. The problem was noticeable when a large portion of the query clip was about a TV studio scene [1]. To tackle this problem, we automatically annotate the master shots along the whole timeline of a video by its dominant concepts, then fold the adjacent shots sharing the same dominant concept. This process is called *story annotation*. With this annotation, we can enhance the result presentation by showing a *context view* of a target shot. Figure 3 is an example. When the query is a common concept/scene, such as an anchor man, we expect multiple relevant shots of the similar scene to appear in the search result (red centered in Fig. 3). Although hardly any decision can be made by the shots themselves, by expanding the result to a *context view* (images with black text underneath), we can easily grasp the story around each shot and thus distinguish these shots. The benefit of story annotation is not limited to the result presentation. In addition, we implement a special *context field* in the query for quickly screening the search result. A user may simply add a few keywords in the context field of the query to refine the search results, eventually coming up with the shots having matched context only. For instance, when querying a report of a flooded village but the query clip is mostly an anchor person in a news studio, other than describing the exact query clip in the system query, we tend to add keywords like *flood*, *rooftop*, *rescue man*, and even *river* (which is visually similar to flood) in the context field.

Acknowledgments. The work described in this paper was supported by two grants from the Research Grants Council of the Hong Kong Special Administrative Region, China (CityU 11210514 and CityU 11250716).

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