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A Review of Video Retrieval Based on Image and Video Semantic Understanding

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Abstract Research trends in new video retrieval based on image and video semantic understanding are presented in this paper. First, recent studies related to image and video semantic analysis are introduced to understand leading-edge multimedia retrieval technologies. Several works related to visualization interfaces for multimedia retrieval are also presented. Finally, trends in state-of-the-art studies and the future outlook are described.

Key words: video retrieval, image and video semantic understanding, visualization, navigation.

1. Introduction

According to the IDC White Paper published in March 2008, the digital universe has reached 281 exabytes and has exceeded the amount of available world-wide storage for the first time¹⁾. It was also reported that not all information created and transmitted gets stored — almost half of the digital data would not have a permanent home in 2011. Furthermore, according to the IDC report published in May 2010, the digital universe is expected to be 44-times larger in 2020 than in 2009²⁾. It was also reported that much of the data included in the digital universe is unstructured data such as images, music and videos, i.e., multimedia data. Thus, the amount of data on the Web is huge, and we are faced with a new problem: how do we find information that we need when we need it? This problem is closely related to new tools for retrieval and discovery.

Currently, users generally use the query-response model to access their desired information on the Web. In the query-response model, the user submits a query through an interface to obtain the desired information. According to the query, this model narrows the huge amount of information down to an amount that the user can check. In this case, the multimedia contents being searched have been annotated with metadata in advance, and the search engine presents the user with the contents whose metadata match the query. Conventionally, metadata include the time and location, which are attached to the content at the time of acquisition,

and manually attached keywords.

In recent years, progress in research of image and video analysis, particularly image and video semantic understanding, has led to the development of technologies that automatically extract metadata³⁾⁴⁾. Machine learning has contributed tremendously to the development of these technologies, especially for deriving semantic level indices, and it is accelerating the progress in content-based image and video retrieval research⁵⁾. Therefore, trends in these research areas are important for understanding recent trends in multimedia retrieval.

Although the accuracy of image and video semantic understanding is increasing, it is still difficult to perfectly solve the problem of the “Semantic Gap”⁶⁾. Specifically, although recent machine learning-based methods can annotate multimedia contents with keywords, they require sufficient amounts of training data, without which highly accurate annotation becomes difficult. In general, it is difficult to provide sufficient training data in all cases, and the accuracy often becomes insufficient. In such cases, since it is difficult to accurately attach the metadata to contents, it also becomes difficult to perform accurate retrieval by calculating inter-content distances or similarities based on metadata.

In addition to the above problems, a new problem has recently emerged. In some cases, we are unable to provide a query that accurately represents the desired content (e.g., keyword, image, etc), and in such cases, finding the desired content through the query-response model becomes difficult⁷⁾. This problem was also pointed out in the IDC report in 2010²⁾. It was also stated in that report that we will have to consider how we find the information we need when we need

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it, and thus new retrieval and discovery tools must be developed. Recently, in order to solve this problem, several studies on “human-centered computing”⁴⁾ have been carried out. In human-centered computing, the main idea is to satisfy users and allow users to make queries in their own terminology. User studies have provided direct insights into interactions between humans and computers. By human-centered, we mean systems that consider the behavior and needs of the human user. The foundational areas of multimedia information retrieval were often in computing-centric fields. Specific examples in this research area include a visualization interface that connects the user and the computer. This is known as the method that provides the most effective solution and is becoming an essential component for realizing more efficient multimedia retrieval.

In this paper, we present research trends in new video retrieval based on image and video semantic understanding. **Figure 1** shows an overview of the recent research trends for video retrieval based on image and video semantic understanding. First, we provide an explanation of existing research related to image and video semantic understanding, which is important for understanding multimedia retrieval. Furthermore, we present an introduction of research trends related to visualization interfaces for multimedia retrieval, which have attracted attention in recent years. The first half of this paper provides details of image and video semantic understanding. Many image and video representation methods, that is, methods for calculating features that can accurately represent contents, have been proposed. Therefore, achievements of methods that have been reported in recent years are described. Furthermore, since collectively investigating classification methods based on extracted features are necessary for image and video semantic understanding, we provide a broad explanation ranging from fundamental methods to the latest machine learning-based methods. In the second half of this paper, details of visualization interfaces for multimedia content retrieval are provided. In addition to achievements of existing studies, recent research trends and the future outlook are described in this paper.

2. Image and Video Semantic Understanding

As described above, image and video retrieval generally becomes feasible by annotating contents with metadata. Researchers foresaw the arrival of the age

of large-scale image and video information retrieval⁸⁾, and research of image and video understanding began. Many of these methods focused on low-level features and enabled retrieval of images in which color or texture features are similar to those of the provided query. However, in order to realize retrieval of content that the user truly desires, high-level features are necessary, and attaching metadata that represent the meaning of the contents is essential. Although in the past, it was considered that realization of such technologies is difficult, corpus-based multimedia analysis methods have been proposed in recent years, and image and video semantic understanding technologies have advanced significantly toward practical use. Examples of leading corpus-based analysis technologies include speech recognition, natural language processing and character recognition. In the field of image and video analysis, by adopting the above approach, methods that can cope flexibly with the diversity and ambiguity of multimedia contents have been realized. The contribution of machine learning is significant. Many features that are effective for image and video semantic understanding have also been proposed. The recent leading methods tend to be extended from those proposed in the field of language processing. These methods are also expected to be highly compatible with statistical machine learning methods.

In this section, methods for representing image and video contents, in other words, recent research trends related to visual features are first explained in Sec. 2.1. Sec. 2.2 provides a broad explanation of statistical models and classifiers utilized for image and video semantic understanding, ranging from fundamental methods to the latest methods.

2.1 Image and Video Representation Methods

Generally, visual features used to represent image and video contents can be broadly divided into two main classes: global features and local features. Global features are calculated from the entire image and include color histograms⁹⁾, HLAC¹⁰⁾, Gist¹¹⁾, etc. These features have been studied since the 1990s and used in content-based image retrieval (CBIR). They realized the retrieval of similar images by searching for similar features in a database. These methods are still used as standard retrieval methods in image and video databases. However, since they utilize low-level features that do not accurately represent the contents, retrieval, which focuses on the objects included in image

and video contents, becomes difficult.

From the late 1990s until the mid 2000s, the use of local features led to a breakthrough that solved the above problem¹²⁾. The most representative use of local feature is SIFT (Scale Invariant Feature Transform) proposed by Lowe¹³⁾¹⁴⁾. This method was proposed for object detection in the presence of an occlusion and provides a new framework for the extraction of feature points and their descriptions. Other methods derived from SIFT, such as PCA-SIFT¹⁵⁾, which performs dimensionality reduction of gradient information via PCA, BSIFT¹⁶⁾, which reduces the effect of background information, and SURF (Speeded Up Robust Feature)¹⁷⁾ have recently been proposed. HOG (Histograms of Oriented Gradients)¹⁸⁾, a feature descriptor for a localized region, has also been proposed. This is widely used in general object recognition, e.g., recognition of humans or vehicles. In the past few years, various methods for performing hierarchical matching based on the above features have also been proposed¹⁹⁾²⁰⁾.

Although the above local features enable accurate and robust description of image and video contents, comparing feature points from many contents becomes difficult when a large number of local features is extracted from a single content. Therefore, a method that retrieves corresponding feature points by quantizing the local feature vector extracted from a single content and replacing it with a codeword that is a representative vector (visual word) has been proposed²¹⁾. The bag-of-features (BoF) representation²²⁾, which allowed application of visual words from specific object recognition to general object recognition, was also proposed and it has become one of the most widely used features in recent years. BoF representation is similar to bag-of-words (BoW) representation, which describes a text document as a vector by ignoring word order and only focusing on the frequency of word occurrence, and it is used in the fields of language processing and information retrieval. BoF representation ignores the location of each feature point and applies the bag-of-words method to visual words. Recently, many extensions of the BoF method have been proposed. Specifically, a method that provides a codebook of visual words based on online clustering and mean-shift²³⁾, a method based on probabilistic clustering through GMM (Generalized Method of Moments) and the EM (Expectation-Maximization) algorithms²⁴⁾, and a method utilizing color and spatiotemporal information²⁵⁾ have been proposed. In the most recent re-

search, a method that utilizes locality-constrained linear coding²⁶⁾ has also been used as an extension of BoF. In addition, bag-of-video-words, a method that applies BoF to video contents, has also been proposed²⁷⁾. An overview of the trends in image and video representation methods is presented in “Visual Features” of Fig. 1.

2.2 Statistical Models and Classifiers

Generally, after the extraction of features representing image and video content (explained in the previous subsection), the content is classified by some statistical models or classifiers. In the past, probabilistic models for performing document classification, such as probabilistic Latent Semantic Analysis (pLSA)²⁸⁾ and Latent Dirichlet Allocation²⁹⁾, have been proposed. These methods are also applied to general object recognition in image and video contents. Similar to the application of BoW representation to BoF representation, these methods are notable examples of adopting methods from the field of language processing. Latent Semantic Analysis (LSA)³⁰⁾ realizes topic extraction by performing singular value decomposition over a collection of feature vectors, and pLSA²⁸⁾, its probabilistic extension, enables the extraction of latent topics. In recent years, LDA²⁹⁾ has been proposed as an expansion of pLSA. Methods that model relationships between heterogeneous features as latent variables (corresponding to latent topics), such as probabilistic canonical correlation analysis (PCCA)³¹⁾, have also been proposed.

In contrast to the above methods, various classification methods that adopt different approaches based on multivariate analysis of the obtained set of features have been proposed. The subspace method³²⁾, the most fundamental method, enables classification by calculating the similarity between the input features and the subspace spanned by the features of each class. In addition, when the input is provided as multiple features, the mutual subspace method³³⁾ enables classification by comparing the subspace of the input and that of each class. Furthermore, the constrained mutual subspace method³⁴⁾ and the whitened mutual subspace method³⁵⁾ were proposed to solve the problem of accuracy degradation due to the overlap between the subspaces of different classes. By using nonlinear subspaces based on kernel principal component analysis³⁶⁾, those methods were respectively extended to the kernel subspace method³⁷⁾, the kernel mutual subspace method³⁸⁾, the kernel constrained subspace method³⁹⁾ and kernel orthogonal mutual subspace method⁴⁰⁾.

SVM⁴¹⁾ has recently become the most well-known machine learning classifier, and it is often used in classification of video content. Support Vector Data Description (SVDD)⁴²⁾ and One-Class SVM (OCSVM)⁴³⁾ are also known as classifiers for one-class problems, where one class problem tries to distinguish one class of objects from all other possible objects. These classifiers have been actively studied, and various extended methods exist. Specifically, the use of kernel methods with classifiers is important for improving classification accuracy, and it is necessary to select the best kernel that is optimal to the subject of application⁴⁴⁾. Also, various methods that aim to improve accuracy by combining multiple kernels have been proposed⁴⁵⁾⁴⁶⁾. In contrast to the above-mentioned methods that construct strong classifiers, methods that realize highly accurate classification by combining weak classifiers trained from large amounts of training data have recently been proposed, with the most notable method being Ada-boost⁴⁷⁾. This method is used in human and face classification, and the VJ (Viola & Jones) method has become one of the most frequently used methods⁴⁸⁾. An overview of the research trends in statistical models and classifiers is presented in “Model and Classifiers” of Fig. 1.

3. Visualization Interfaces for Image and Video Retrieval

As shown in the previous section, recent developments in image and video semantic understanding have contributed significantly to improvement in the accuracy of image and video retrieval technology. It should be noted that existing systems that perform retrieval are based on the Query-Response model, and there is a large number of systems displaying search results based on the similarity between query content and contents in the database. However, it becomes difficult for those systems to provide useful information to users due to the semantic gap or in cases in which users cannot provide accurate queries. Note that the semantic gap generally means the difference between visual features extracted from image and video data and high-level information of humans. In recent years, general studies related to human-centered computing⁴⁹⁾⁵⁰⁾ have been performed to address this problem. Visualization systems (also known as navigation systems)⁵¹⁾ have been developed and are expected to become an alternative to the Query-Response model.

3.1 Existing Research Trends

Many visualization methods for image and video retrieval have been proposed. As shown in “Visualization Interface” of Fig. 1, conventional methods for visualizing large amounts of retrieved contents are broadly divided into three main classes: dimensionality reduced mappings, clustering-based visualizations and graph-based representations⁵²⁾⁵³⁾. Methods based on dimensionality reduced mappings calculate the similarities between contents in a high-dimensional feature space and represent them in lower-dimensional spaces, i.e., visible dimensional (2D or 3D) spaces. Then users can easily understand the similarities between the visualized contents. Since these methods perform a mapping from a high-dimensional feature space to a low-dimensional feature space, conventional dimensionality reduction methods from the field of multivariate analysis are often adopted. A browsing method⁵⁴⁾ based on dimensionality reduction using PCA, an MDS (Multi-Dimensional Scaling)⁵⁵⁾-based browsing method⁵⁶⁾, and also an SOM (Self-Organized Maps)⁵⁷⁾-based method⁵⁸⁾ in which SOM enables non-linear mappings have been proposed. Furthermore, in the past ten years, several methods based on ongoing research related to Manifold Learning, such as ISOMAP (isometric mapping)⁵⁹⁾, SNE (stochastic neighbor embedding)⁶⁰⁾ and LLE (locally linear embedding)⁶¹⁾, have been proposed.

In clustering-based visualization, in order to enable users to instantly grasp the entire contents being searched, the amount of contents is reduced by grouping similar contents. In this case, content similarity can be calculated on the basis of data such as features extracted from the image contents⁶²⁾⁶³⁾, metadata⁶⁴⁾ and the content acquisition time⁶⁵⁾. Then users can retrieve the desired contents by narrowing down from the representative contents of each cluster.

On the other hand, graph-based representations enable the visualization of content collection by constructing a graph. In these approaches, the contents are regarded as nodes, and two nodes with a high similarity are connected by edges. Furthermore, in these approaches, similarities are calculated on the basis of content’s features⁶⁶⁾ and shared-keyword annotation⁶⁷⁾.

In addition to the above three broad classes, various visualization methods have been proposed, and methods that share different classes also exist⁶⁸⁾⁶⁹⁾. Many good surveys of image and video visualization and navigation have been published⁵²⁾⁵³⁾⁷⁰⁾⁷¹⁾⁷²⁾.

3.2 Recent Research Trends and Future Outlook

As shown in the previous subsection, the use of visualization can overcome the limitations of conventional retrieval systems. By developing mutually, the fields of image and video semantic understanding and visualization have enabled the provision of higher-level multimedia content retrieval to users. Therefore, as shown in “Recent Trends” of Fig. 1, research areas that realize acceleration for each field have progressed rapidly in recent years. Specifically, an extremely large number of methods that perform image and video semantic understanding and visualization follow the multimodal approach⁷³⁾. Video content includes visual and audio data (and sometimes includes closed captions), and it has been shown that their collaborative use can lead to improvement of retrieval accuracy. In practice, there are various methods that realize the improvement of retrieval accuracy by introducing a multimodal approach⁷⁴⁾⁷⁵⁾⁷⁶⁾. In the field of image and video semantic understanding, there have also been attempts to apply multimodal processing to statistical models or classifiers⁷⁷⁾. When targeting content on the Web, new approaches that use text data from the Web page including that content and inter-page link relationships have also been proposed⁷⁸⁾.

In the field of image and video retrieval, including visualization, some trials to improve retrieval accuracy through interactions with the user have also been carried out. The leading method is RF (Relevance Feedback), which utilizes feedback from the user to interactively bring the search results closer to the desired content⁷⁹⁾. In practice, the RF method has been actively introduced to the field of video retrieval and is used in several methods shown above⁷⁵⁾⁷⁶⁾. Furthermore, through a similar way of thinking, Associative Search⁸⁰⁾ used with text data has been introduced to video retrieval⁸¹⁾. Even if users cannot provide accurate queries, these methods repetitively select a new query from the retrieval results, gradually increasing retrieval accuracy and finally leading to the desired information. A good survey on Interactive Search is provided in a reference⁸²⁾ since a number of approaches are introduced.

As described above, the fields of image and video semantic understanding and visualization are very closely related to each other in multimedia retrieval. However, there has been a tendency for them to develop as independent fields. The birth of a new research area that crosses these fields is expected in the future.

4. Conclusion

In this paper, research trends related to new video retrieval based on image and video semantic understanding have been presented. Recent trends related to visualization interfaces for new multimedia retrieval that have been researched in recent years have also been introduced. By applying multimedia technology, which is realized by fusing various research fields, new services will be created. In the future, it is expected that a diverse range of services will be developed.

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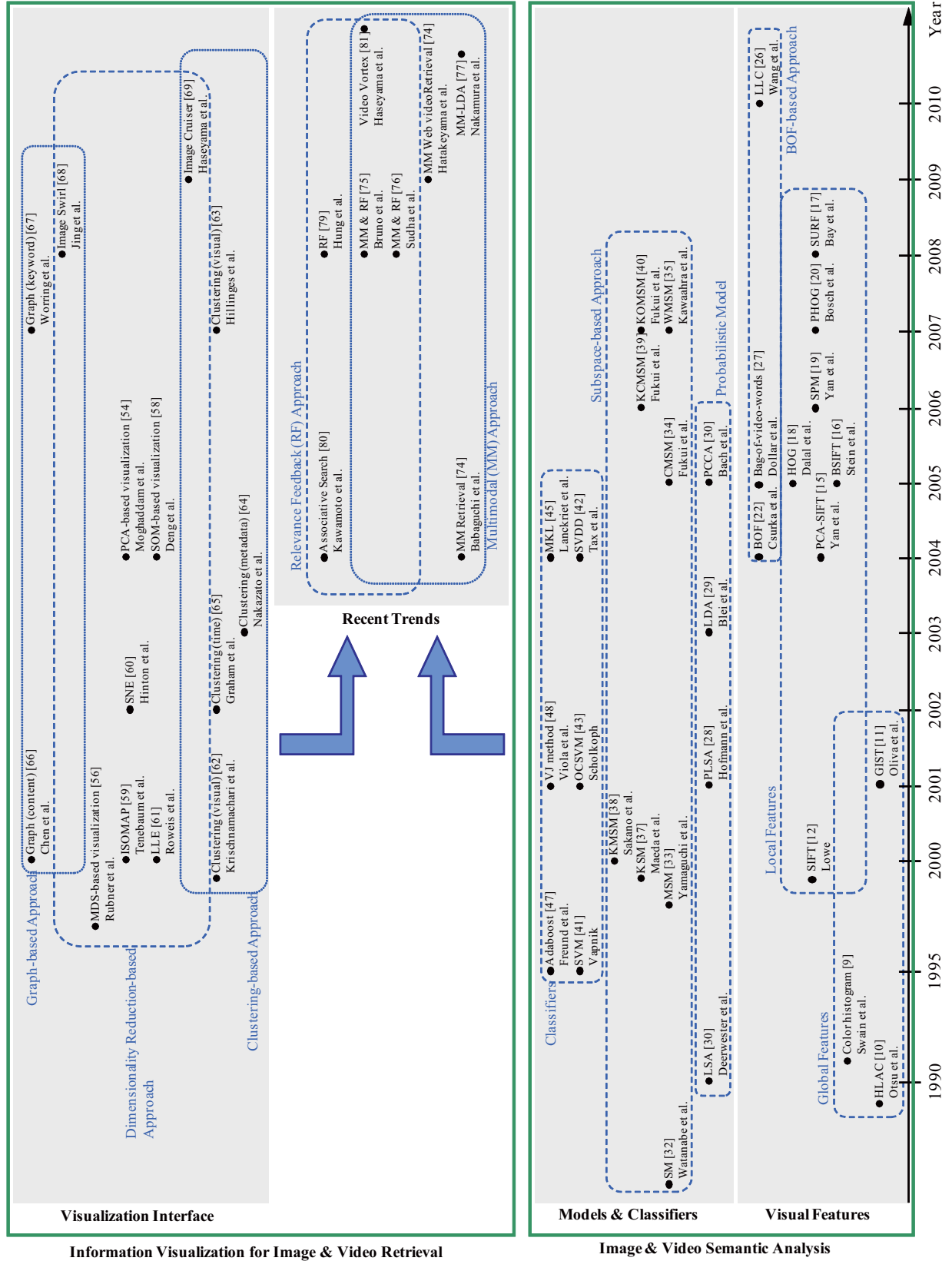


Fig. 1 Overview of recent research trends for video retrieval based on image and video semantic understanding.