A Generic Approach for Systematic Analysis of Sports Videos

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Various innovative and original works have been applied and proposed in the field of sports video analysis. However, individual works have focused on sophisticated methodologies with particular sport types and there has been a lack of scalable and holistic frameworks in this field. This article proposes a solution and presents a systematic and generic approach which is experimented on a relatively large-scale sports consortia. The system aims at the event detection scenario of an input video with an orderly sequential process. Initially, domain knowledge-independent local descriptors are extracted homogeneously from the input video sequence. Then the video representation is created by adopting a bag-of-visual-words (BoW) model. The video's genre is first identified by applying the k-nearest neighbor (k-NN) classifiers on the initially obtained video representation, and various dissimilarity measures are assessed and evaluated analytically. Subsequently, an unsupervised probabilistic latent semantic analysis (PLSA)-based approach is employed at the same histogram-based video representation, characterizing each frame of video sequence into one of four view groups, namely closed-up-view, mid-view, long-view, and outer-field-view. Finally, a hidden conditional random field (HCRF) structured prediction model is utilized for interesting event detection. From experimental results, k-NN classifier using KL-divergence measurement demonstrates the best accuracy at 82.16% for genre categorization. Supervised SVM and unsupervised PLSA have average classification accuracies at 82.86% and 68.13%, respectively. The HCRF model achieves 92.31% accuracy using the unsupervised PLSA based label input, which is comparable with the supervised SVM based input at an accuracy of 93.08%. In general, such a systematic approach can be widely applied in processing massive videos generically.

Categories and Subject Descriptors: H.3.1 [**Information Storage and Retrieval**]: Content Analysis and Indexing—*Abstract methods*; *indexing methods*

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1. INTRODUCTION

Living in the information era, we are surrounded by an enormous scale of digital contents. According to Bohn and Short [Bohn and Short 2010], the estimated size of newly created digital data in 2011 is about 1,800 exabyte (1 exabyte = 1 billion gigabytes), roughly 100 times of the production in 2002 ($2 \sim 3$ exabyte). This is equivalent to a ten-fold annual growth rate on average. In terms of image and video content, YouTube has 73M videos uploaded every year at a rate of 15 hrs/min, while the number of digital images on the Internet is about 5 billion, in which only 5%–10% of them are labeled [Yan and Hsu 2009].

Among this explosive growth of multimedia data, sports videos contribute significantly to the total collections of the digital content. Analysis of sports videos has drawn more and more attention in the research community due to its huge popularity and vast commercial value. Sources of sports video collections are various: from daily-basis public recreations to professional sports games broadcasting; from amateur digital camcorders to professional TV broadcasting; and plenteous but low-quality online streamed videos. Most of the literature works focus on particular sports and tasks, utilizing domain knowledge and production rules. [Ekin and Tekalp 2002; Nepal et al. 2001; Xu et al. 2001; Xu and Li 2003; Zhu et al. 2009]. Supervised learning is another important characteristics adopted by these works to fill the semantic gap. Although aforementioned methods have their merits and brilliance, most of them are stand-alone with little interconnection. They also suffer from a lack of generality and scalability to large-scale data for two reasons. First, with various video contents of different themes and cinematographic techniques, domain knowledge-associated methods have difficulties in extensibility. Second, labeled data is required for supervised learning, while the majority of multimedia data currently available is unlabeled. In order to tackle these two issues in sports videos, our proposed approach focuses on developing a domain knowledge-independent feature selection and video representation with an unsupervised learning technique.

In this article, a generic and systematic framework is proposed with experimentations on a relatively large-scale sports video dataset. We use the term *relatively large-scale* to accurately describe this dataset we engaged with, which is not truly large-scale, but has the same complexity of video types and contents. Three tasks are introduced in a systematic and generic manner such that the output from the previous tasks are utilized as the input to the next task. Event detection is the third and final quest with two preceding tasks: video genre categorization and semantic view type classification. By accomplishing these three tasks, an event detection can be achieved with minimum domain knowledge and insufficient labeled data.

The contribution of this paper is twofold.

(1) A comprehensive survey is conducted targeting existing works of sports video analysis from aspects of low-level genre, middle-level views/shots, and high-level semantics. Individual literature works have their own merit and credit in the field, either focusing on a generic method using probabilistic modeling, for instance, or focusing

on a systematic approach. However, emphasizing the generic property tends to be a nonsystematic approach, while pursuing a systematic approach is prone to ignore generality.

(2) An awareness of such a deficiency during the survey study leads us to the proposed work: a generic and systematic approach on analyzing sports videos. This is the second contribution of this article, which can be further divided into the following three subcontributions. (2.1) Initially, domain knowledge-free local descriptors are extracted using a homogenous process. A bag-of-visual-words (BoW) model is used to build a histogram-based distribution to represent video clips. The BoW model with local features is a natural selection for generically processing videos due to its domain knowledge-free property. (2.2) Subsequently, since unlabeled data comprises the major portion of all digital content, an unsupervised classifier taking the homogeneously processed representation of part (2.1) is preferred such that an automatic and systematic process can be deployed towards a large-scale dataset. Since sports videos have well defined semantic view types from their production characteristics, local features and the BoW model are perfect candidates in view classification, as has been proven successful in computer vision and object recognition fields. Therefore, a probabilistic latent semantic analysis (PLSA)-based method for semantic view classification is preferred due to its unsupervised nature and fit with the BoW model input. (2.3) Lastly, a structured prediction model is a suitable for taking labeled middle-level agents as input to achieve high-level semantics. This is because sports videos have distinguishable temporal patterns often consisting of sequences of middle-level agents. In our work, since semantic view types have been classified in part (2.2), an appropriate approach is to take view results as input for achieving semantic events detection. Therefore, hidden conditional random field (HCRF) is introduced as a rational choice. The significance of the HCRF is its generalized modeling, which resides in both the relaxation of the Markov property and incorporation with hidden states of the conditional random field (CRF) modeling.

The rest of this article is organized as follows. In Section 2, an extensive review in video analysis is provided. An overview of the proposed system with a flowchart is given in Section 3. Proposed techniques achieving various tasks are addressed in the next three sections. The generic feature extraction, the BoW model using the proposed bottom-up structure in codebook generation, and the genre categorization technique are presented in Section 4. In Section 5, middle-level view classification is analyzed by adopting the PLSA-based unsupervised model. Section 6 presents a discriminant HCRF structured prediction model on high-level event detection. Experimental results are given in Section 7. Finally, the article is concluded in Section 8.

2. RELATED WORKS

This section reviews the related works in the domain of sports video analysis. This survey appreciates each individual work for its contribution and value to the research field. Although various researches reviewed in this work are inspirational and innovative, there is a lack of work focusing on a holistic aspect from an angle of generality and systematic property. Most of the literature works focus on a single aspect. Some works focused on specific sport types with sophisticated techniques. Some researches targeted generic approaches but lacked systematic analysis. Other works proposed systems with automatic processes, but lacked generic and scalable properties. In the following, we are going to examine both the merits and disadvantages of the literature works in the following order, from low-level feature extraction with video genre categorization to middle-level view classification to high-level semantic event detection.

Table I. Summary of Previous Video Genre Categorization Methods

Authors and Year Published	Number of Genres	Size of Database (hrs)	Domain knowledge		Genre Categorization Method	Accuracy rate
			Object-Based	Cinematic-Based		
[Truong et al. 2000]	4	8	Yes	Yes	C4.5 decision tree	83%
[Takagi et al. 2003]	6	33.75	Yes	Yes	statistics-based	n/a
[Xu and Li 2003]	5	5	Yes	No	PCA & GMM	86.5%
[Jaser et al. 2004]	4	n/a	Yes	Yes	decision tree and HMM	91.6%
[Wang et al. 2006]	3	16	No	Yes	pseudo-2D-HMM	n/a
[Yuan et al. 2006]	6	33.33	No	Yes	hierarchical SVM	94%
[Glasberg et al. 2008]	5	5	Yes	Yes	Multimodel	88.5%
[Montagnuolo and Messina 2009]	8	100	Yes	Yes	Parallel Neural Networks	95%

2.1. Genre Categorization

Video genre and its categorization was one of the earliest video analysis to draw researchers' interest. The main task of this genre categorization starts from different big groups of videos, such as sports, music, news, movies, etc., and gradually moves to more delicate categorization, such as identifying the sports types. Various works have been highlight, in the following. However, a major and common disadvantage of these works is their heavy dependency on domain knowledge.

Fischer et al. [1995] first proposed a classification method based on five different video genres. Brezeale and Cook [Brezeale and Cook 2008] provided an extensive survey in this field. Incorporating the survey and the most recent works, a concise summary is provided in Table I. Color features with C4.5 decision trees were used in Truong et al. [2000]. Camera motion feature with statistical classifiers were chosen to classify six sports genres in Takagi et al. [2003]. A principal component analysis (PCA)-modified audio-visual feature was used to train a Gaussian mixture model (GMM) classifier in Xu and Li [2003]. Semantic shots (views) were used to help in genre categorization in Jaser et al. [2004]. Motion and color, as well as audio features, were applied in Wang et al. [2006]. Color features with a hierarchical support vector machine (SVM) were used in Yuan et al. [2006]. High-level MPEG-7 features were extracted and applied in multimodality classifiers in Glasberg et al. [2008]. The best classification result at the moment is with an accuracy of 95% using a dataset of eight different genres [Montagnuolo and Messina 2009]. These methods used various domain knowledge with supervised classifiers to achieve the automatic genre categorizations.

As defined in Ekin et al. [2003], domain knowledge-based features can be divided into two categories: cinematic-based features and object-based features. The cinematic feature involves middle- to high-level semantics from common video composition or production rules, such as shots/views or events, while object-based features are described by their spacial property, such as color, shape, and texture, as well as spatial-temporal-based object motions. As Table I shows, all reviewed works are domain knowledge-dependent and either object-based or cinematic-based. A lack of diversity, that is, the number of different genres in the database, restricts these methods from generality.

2.2. View Classification

Views (shots) are considered middle agents to link low-level features and high-level semantic events [Duan et al. 2003; Ekin and Tekalp 2002]. Supervised approach is a favorite choice in the research community. Although the labeling effort is not the primary concern because of the size and diversity dealt with by current research; such

Table II. Comparison of View Classification Techniques in Literature, Emphasizing Features Utilization and Classification Methods

Authors and Year Published	Nature of data	Global Features			Local Feature-Based	View Classification Method
		Color-Based	Texture-Based	Others (yes/innov)		
[Xu et al. 2001]	Soccer	Yes	No	No	No	thresholding (*S*)
[Ekin and Tekalp 2002]	Soccer	Yes	No	Yes	No	morphological operations (*S*)
[Duan et al. 2003]	4 Sports	Yes	Yes	innov	No	Decision Tree (*S*)
[Tong et al. 2004]	Soccer	Yes	Yes	Yes	No	Decision Tree (*S*)
[Wang et al. 2007]	4 Sports	Yes	Yes	Yes	No	spectral clustering (*UnS*)
[Benmokhtar et al. 2008]	Soccer	Yes	Yes	Yes	No	Neural-network (*S*)
[Zhong et al. 2008]	3 Sports	Yes	No	No	No	Spectral-division algorithm (*UnS*)
[Kolekar and Palaniappan 2009]	Soccer	Yes	No	Yes	No	Decision Tree (*S*)

Note: In the "Global Features" column in the "Others (yes/innov)" category, "yes" means other than color and texture global features are used while not innovative, while "innov" means newly designed features are used. For the "View Classification Method" column, *S* indicates a supervised method, while *UnS* indicates an unsupervised method.

task becomes more and more unaffordable parallel with the growth of the dataset. Therefore, approaches using unsupervised learning techniques with generality and efficiency ought to be sought for analyzing large-scale multimedia consortia. We summarize related works so that readers can compare popular supervised means with proposed unsupervised PLSA in this article. Additionally, there are only two works using unsupervised techniques sought by our extensive study; we present them for completeness of the review [Wang et al. 2007; Zhong et al. 2008].

Although there may be different nomenclatures, the fundamental purpose of the middle-level views (shots) is to involve certain production rules to help high-level tasks. This frame-based label concept was first introduced by Xu et al. [2001], who defined three groups of views: global, zoom-in, and close-up. Ekin and Tekalp [2002] used a slightly different long-shot, middle-shot, and close-up/out-of-field notation. [Duan et al. 2003] used a finer view/shot groups classification supported by innovative semantic features. These pioneering methods, along with other works such as Tong et al. [2004], Wang et al. [2005], and Kolekar and Palaniappan [2009] focus on using decision tree classifiers to link the low-level features to view/shot types. Xu et al. [2001] and Ekin and Tekalp [2002] applied color-based grass detector and field/object size to determine view types. Incorporating previously mentioned features, Tong et al. [2004] added head-area detection as well as a grey-level cooccurrence matrix(GLCM) to improve the decision tree on classification. Wang et al. [2005] used field region extraction, object segmentation, and edge detection for view-type decision making. Duan et al. [2003] first extended the research from single genre (soccer) to multiple genres (four sports) using individual genre-based decision trees. Different from previous visual feature extraction methods, Kolekar and Palaniappan [Kolekar and Palaniappan 2009] took a top-down approach. They first used audio features to find exciting video clips. Subsequently, the motion features of the whole image volume along with the background color information are then used for view-type classification. Benmokhtar et al. [2008] took an approach on feature-level fusion using dynamic PCA with information-coding neural network (NN). At the classification level, another NN is used to fuse multimodality inputs. However, these supervised methods are limited by the labeled data and, thus, constrained from expanding to larger scales.

Some other researchers pursued unsupervised methods for view classification. Wang et al. [2007] proposed an information-theoretic coclustering method in which

mutual information was maximized by treating shot classes and features as two random variables. As a consequence, color histograms and perceived motion energy features are used with a test set of four sports video genres. Zhong et al.'s method was inspired from spectral theory conventionally used to solve segmentation in graph theory [Zhong et al. 2008]. They proposed a spectral division algorithm to find the proper video shot clustering, which were tested in three sports videos using HSV space color feature. Although good performances have been obtained in these methods, the extensibility and flexibility towards diverse genres and large-scale datasets are very limited. This is again due to the domain knowledge dependency of the extracted features.

Table II compares the aforementioned methodologies from angles of feature utilization and classification techniques. Color and texture are two major global features used by most works. Duan et al.'s work is the only one proposing middle-level features developed from low-level global features. The rest of the works either adopted additional popular global feature schemes, such as audio feature or Gabor feature, as well as some production rule-based features, or didn't utilize any. While various global features are used, none of the local features have been applied. Moreover, most of the supervised methods (except Duan et al.'s work) focus on a single-type (soccer) sport, while unsupervised techniques employed various sports types.

2.3. Event Detection

As one of the most popular semantic tasks in video analysis, event detection has been a popular topic from the beginning of multimedia research. Despite different definitions of event detection by different researchers, commonly acknowledged properties of an *event* can be summarized as follows. An event occupies a period of time and is described using the salient aspects of the video sequence input, which consists of smaller semantic units or building blocks [Lavee et al. 2009]. Lavee et al. also summarized and classified event detection algorithms into three categories: a) pattern-recognition models, b) semantic event models, and c) state event models. Pattern-recognition models focus on direct classification from low-level features but lack semantic linkage. Semantic models target high-level semantic rules and constraints with domain knowledge. This requires a lot of human involvement in creating rules and regulations using prior information. State models utilize abstracted middle-level agents as well as the intrinsic structure of the event itself.

By comparing these three categories of event modeling with examples in literature, we think that the pattern-recognition model is heavily dependent on classifiers, which at the moment, are not intelligent enough to understand all semantics from low-level features. On the other hand, the semantic model considerably relies on human expertise and thus underestimates the accuracy and efficiency provided by classification tools. From our experience, the state model incorporates the strength of pattern recognition at low-level with classifiers at high-level so that it utilizes both feature-extraction power and classification intelligence. Moreover, the state model also accommodates an automatic process and unsupervised learning, which reduces human input into the system. Therefore, state event models are suitable for analyzing large-scale datasets from both generic and systematic point of views. A coarse-to-fine strategy fits well into such state event models by first roughly localizing the event with context information and then precisely detecting the event using an advanced structure model. A detail description is presented in Section 6.

Although we prefer the state event model for its natural fit to the proposed systematic approach in this work, two other models are still appreciated for their efficiencies in analyzing sports videos and utilizations in other applications. In the following, state-of-the-art works are summarized and compared.

Support vector machine (SVM) is a popular pattern-recognition model approach [Lavee et al. 2009]. Some groups use rich audiovisual features, such as face detection, scoreboard information, as well as geometry of the field, to find certain semantic events. Sadlier and O'Connor [2005] used SVM to classify scoring events for four different field sports. Xu et al. [2003] analyzed tennis videos by using hierarchical-SVM applied on fused audio-visual modalities. Similarly, Ye et al. [2005] utilized middle-level view labels as well as shot length and camera motions descriptors. An SVM-based incremental learning scheme using updated data is proposed in detecting soccer events, along with a predefined temporal structure. A similar approach combining SVM and predefined temporal structure was proposed by Li et al. [2009] targeting basketball events using optical flow patterns.

Some semantic event models using rules and logic and semantic relationships are presented. Babaguchi et al. [2002] used closed caption text streams with audiovisual features and the intermodal correlation between them to search a "touch down" event from four hours of American football videos. Zhang and Chang [2002] also focused on superimposed caption frames and used decision trees to decide the event, such as "scoring" or "last pitch" for baseball games. Ekin et al. [2003] incorporated production rules and soccer sport rules to detect certain events such as "goal", "referee", and "penalty-box".

In terms of state event models, one of the earliest works targeting structures of videos was from Nepal et al. [2001], who empirically studied the temporal model in basketball videos based on manual observation, using heuristic methods and low-level audiovisual features. Duan et al. [2003] also created a temporal structure using multimodality with heuristic experience on tennis events. Another approach of learning temporal structure is from the data mining perspective, where Tien et al. [2008] focused on tennis match events detection by creating a max-subpattern tree and learning the frequent patterns from it.

Another important branch of state event models are structured prediction models such as hidden Markov models (HMMs) and their variations, Bayesian networks, as well as discriminative conditional random fields (CRFs). Zhang et al. [2007] proposed an HMM-based statistical method for classifying middle-level agents generated from webcasting texts. Tong et al. [2004] used Bayesian networks to classify "shoot" and "card" events in soccer videos by applying decision tree-based intermediate-layer concept units. Mei and Hua [2008] proposed an innovative mosaic-based middle-agent for key-event mining using HMMs. Wang et al. [2006] proposed a CRF model on detecting semantic soccer events, and the performance turned out to be better than that of both SVMs and HMMs. A similar approach was also proposed by Xu et al. [2008] using CRFs for basketball and soccer event detection where a webcast text feature was obtained to achieve middle-level concepts. An interesting event tactic analysis is proposed by Zhu et al. [2009] which is beyond the conventional event and adopts the cooperative nature and tactic patterns of team sports. Extensive experiments have been conducted on soccer.

Table III provides a comparison of the aforementioned literature works from a feature utilization point of view. Most of the methods utilize the multimodality schemes of features input. By comparing the number of events processed, it appears that the state event model has better scalability in examining various event scenarios. It is also interesting to point out that the local visual feature hasn't been utilized in any of the methods. In addition, many of the methods, especially the state event models, require middle-level semantic agents to bridge the gap between the low-level features and the high-level events. Such middle-level agents have to be labeled data. However, for the generic approach presented in this work, we tackle the event detection problem using the input obtained by unsupervised learning and unlabeled data.

Table III. Comparison of Event Detection Models Emphasizing Feature Utilization from Both Low-Level Features and Middle-Level Semantic Agents

Event-Detection Algorithm Category	Authors and Year Published	Nature of Data	Number of Events	Low-level Multimodal Features	Visual Features		Middle-level Semantic Agents
					Global-Based	Local-Based	
Patten-Recognition Model	[Xu et al. 2003]	Tennis	5	AVM	Yes	No	Yes
	[Sadlier and O'Connor 2005]	4 field sports	2	AVS	Yes	No	No
	[Ye et al. 2005]	Soccer	1	n/a	n/a	n/a	Yes
	[Li et al. 2009]	Basketball	5	VM	Yes	No	No
Semantic Event Model	[Babaguchi et al. 2002]	Football	3	VST	Yes	No	No
	[Zhang and Chang 2002]	Baseball	2	VT	Yes	No	No
	[Ekin et al. 2003]	Soccer	3	VS	Yes	No	Yes
State Event Model	[Nepal et al. 2001]	Basketball	1	AVMT	Yes	No	No
	[Duan et al. 2003]	Tennis/Soccer	16	AVMT	Yes	No	Yes
	[Tong et al. 2004]	Soccer	2	VM	Yes	No	Yes
	[Wang et al. 2006]	Soccer	5	AVM	Yes	No	Yes
	[Zhang et al. 2007]	Basketball	5	VT	Yes	No	Yes
	[Tien et al. 2008]	Tennis	4	AVS	Yes	No	No
	[Mei and Hua 2008]	Soccer	3	VM	Yes	No	Yes
	[Xu et al. 2008]	Soccer/Basketball	17	VTS	Yes	No	Yes
	[Zhu et al. 2009]	Soccer	6	VMTS	Yes	No	Yes

Note: In the "Low-level Multimodal Features" column, various features are utilized, including audio (A), visual (V), text (T), motion feature (M), and video shot detection (S), as well as an "n/a" label in the case when no low-level features are mentioned in the related works.

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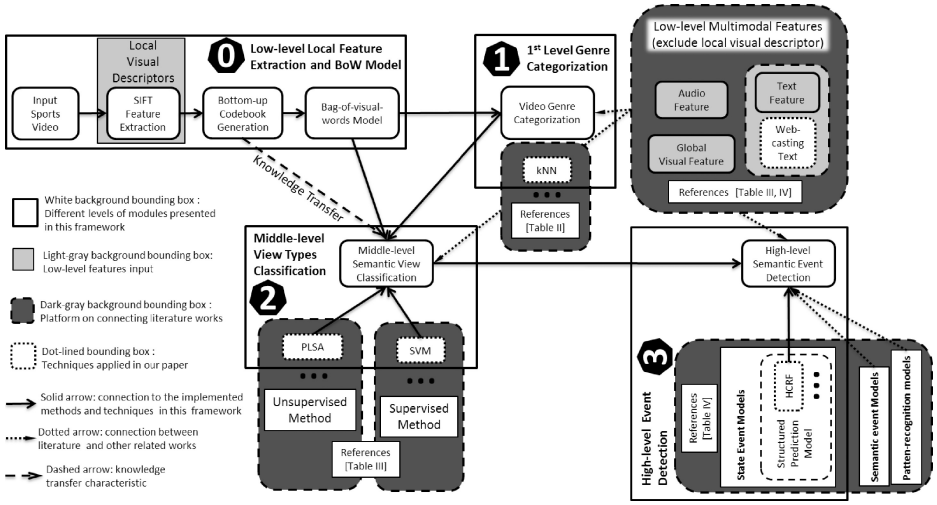


Fig. 1. A flowchart of the proposed generic framework with one module of generic video representation and three task modules in sequence. Besides the three-level modules in the white background bounding boxes, this framework also highlights the relationship between our system and existing literature works, which are shown in the dark gray background bounding box. Associated table references are also indicated in each module. Multimodal features excluding local visual features are also introduced at various stages by literature works. The dotted arrows are used to represent these associations. The solid arrows denote the proposed and implemented techniques in our work. The dashed arrow represents a knowledge transfer characteristic of the generated codebooks. In summary, codebooks generated from certain sports with abundant resources, can be transferred and utilized in classifying other sports materials with scarce resources. The detail analysis is introduced in the section 7.2.

3. OVERVIEW

This section provides a system overview from a holistic aspect as illustrated in Figure 1 such that the input sports video is analyzed systematically using a generic and sequential framework. This is interpreted such that the result from a preceding process is the input to the next process with a consistent and coherent fashion. There are four modules in total: while modules 1–3 are tasks introduced in this work, module 0 is the infrastructure effort in generic low-level feature extraction and video representation. The highlights of this framework include the following.

(1) A generic foundation using domain knowledge-free local features is developed to represent input sports videos. This method fits the general framework in sports video analysis and provides an alternative solution to alleviate generality, scalability, and extension issues.
(2) A thorough and systematic structure starting from genre identification is presented, which was ignored in some related works that assumed the genre type as prior knowledge.
(3) A general platform is introduced to associate our approach to abundant and valuable existing literature works, as well as various and innovative features input.

At module 0, the low-level local feature utilization incorporating with codebook generation and the BoW model provides an expandable groundwork for the semantic tasks of genre categorization, view classification, and high-level event detection. As our survey shows, the local feature is rarely explored in the domain of the sports videos, though it has been broadly adopted and proven effective in the field of computer vision. Most of the literature involves domain knowledge and production rules at the

feature-extraction level. In our structure, a homogenous process is first introduced for extracting domain knowledge-independent local descriptors. A BoW model is used to represent an input video by mapping its local descriptors to a codebook, which is generated from an innovative bottom-up parallel structure. The histogram-based video representation is treated as the sole input (no other feature models) to both the genre categorization and the view classification modules. Such a concise representation built from the BoW model benefits users in homogenously extracting visual features and representing videos in a compact and collective form.

At the 1st module, videos are categorized by genre. Video genre nomenclature is used to describe the video type, which is defined as the highest level of granularity in video content representation. Since the video genre categorization task directly relies on low-level features, the proposed feature extraction of the target video sequence is used in categorization. In large-scale videos, a successful identification of the genre serves as the first step before attempting higher-level tasks. For instance, in sports event detection, an unknown "shooting" event is the target quest, which could be from a ball game or a shooting sport. By indiscriminately treating the entire dataset, this event will be searched for in all types of sports. However, since sports like figure skating and swimming have no "shooting" at all, the effort in searching this event within those nonrelevant sports becomes infeasible. Instead of treating all data indifferently, a more efficient approach is to identify the genre of the query video first and then deploy middle/high-level tasks consequently. As the survey shows in sports video analysis, most of the related works on view classification and event detection assume the genre by default. This framework, however, provides a system that automatically identifies the genre from various types of sports data before further analysis.

In the middle-level and 2nd module, semantic view types are classified using an unsupervised PLSA learning method to provide labels for input video frames. *View* describes an individual video frame by abstracting its overall content. It is treated as a bridge between low-level visual features and high-level semantic understanding. In addition, unsupervised learning saves a massive amount of human effort in processing large-scale data. Moreover, the supervised methods can also be implemented upon our proposed platform. Therefore, a SVM model is executed as the baseline for the comparison purpose.

Finally, at the 3rd module, a structured prediction HCRF model using labeled inputs is a natural fit for the system in detecting semantic events. This can be justified in that a video event occupies a various length along the temporal dimension Thus, the state event model-based HCRF is suitable to deploy. Less comprehensive baseline methods, such as the hidden Markov model and the conditional random field, can also be applied on this platform.

In the following section, module 0 and module 1 are combined and presented, including feature extraction, bag-of-visual-words model, as well as genre categorization.

4. FEATURE EXTRACTION, BAG-OF-VISUAL-WORDS MODEL, AND GENRE CATEGORIZATION

This section covers the first part of our proposed framework, generic feature extraction with the BoW model, and systematic genre categorization. Figure 2 illustrates details of each process.

4.1. Feature Extraction

Local invariant features are chosen for homogenous feature extraction due to their domain knowledge-free property. The scale, rotation, and illumination invariant properties make these descriptors good candidates in preserving the similarities for

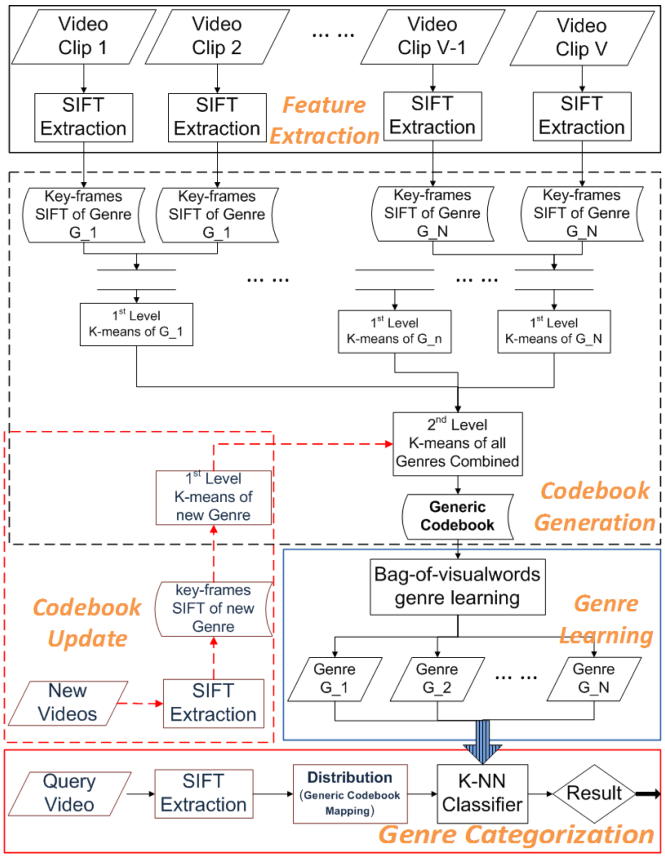


Fig. 2. Feature extraction and genre categorization framework using data parallelism and bottom-up structure for codebook generation.

semantic objects and events matching and detection. Global features, on the other hand, rely on domain knowledge and have difficulties in robust concept and event detection, especially in the presence of noise and occlusion [Jiang et al. 2010]. Scale-invariant feature transform (SIFT), developed by Lowe, is selected as feature descriptors in this work [Lowe 2004]. The SIFT method extracts key points of an image and describes these points using local neighborhood regional information. Since no prior and domain knowledge is required, SIFT is an ideal option in the large-scale automatic and homogenous process. By processing image sequences sampled from video clips, each frame is represented by a magnitude of hundreds of SIFT descriptors. After homogenous local descriptor extraction, the BoW model is applied, whose effectiveness relies on a robust codebook design. In order to achieve this resiliency, we propose a two-level bottom-up K-means clustering for codebook generation. The advances of the bottom-up structure are efficiency, scalability, and robustness.

4.2. BoW Model with Two-Level Bottom-Up Codebook Generation

BoW is a widely recognized model for successfully utilizing key point-based local features and has shown great results in concept detections of images [Jiang et al. 2010; Lay and Guan 2006; Yang et al. 2007]. A representative codebook is synthesized

using codewords which are exemplars of combining all SIFT descriptors. A video clip is then characterized by mapping its SIFT feature points to the generated codebook and a histogram distribution is obtained. This compact representation preserves the information with a small size in storage. In addition, random noisy features can be suppressed in terms of a frequency-based histogram representation.

With the large-scale dataset, efficiency and robustness of the codebook formation have been important concerns for the BoW model. Heuristically, the larger the codebook size, the better the classification results (with certain saturation limitations) [Philbin et al. 2007; Yang et al. 2007]. Different codebook sizes have been explored, ranging from several hundred [Lazebnik et al. 2006; Zhang et al. 2007] to thousands [Sivic and Zisserman 2003] to hundreds of thousands [Philbin et al. 2007]. Since they all used different datasets, there is no conclusion drawn for a decision rule. In this article, choices of codebook sizes are based on empirical studies.

K-means clustering is utilized to generate a codebook by finding and appointing cluster centers as codeword values. In a large-scale domain, satisfactory performance has been reported using a top-down structure for categorization [Li et al. 2009]. In that work, a two-layer top-down structure is used for sports genre categorization. At the first layer, a general codebook (size 800) is generated using single K-means, in which a query video is only categorized to one of the predefined bigger groups consisting of several genres. Such a group is determined by those sports sharing similar semantics. At the second layer after a bigger group belonging is identified, an individual codebook (size 200) for this bigger group is used to decide the video genre. For instance, judo and boxing are combined into a bigger group named martial arts, where martial arts is used as the first-layer candidate. Subsequently, judo and boxing are differentiated in the second-layer categorization. Although good classification accuracy has been reported, efficiency and robustness are problems of such a method in creating a general codebook using single K-means clustering. This is because most computation of K-mean's lies in calculating the distances between individual points to their cluster centers in each iteration. A single K-means clustering using large-scale data is heavy in computation and sometimes inaccurate due to K-means, own limitations. Since more than 3 million high-dimensional SIFT points are used for building the codebook in our application, one single K-means clustering becomes inefficient.

Therefore, a two-level bottom-up structure is proposed in this work for efficient codebook generation. At the bottom structure, individual genre codebooks are generated in 1st-level K-means clustering. At the upper structure, the 1st-level codebooks are used as the input for the 2nd-level K-means to create the generic codebook. By using this bottom-up structure, we reduce the heavy computation in measuring individual point-to-cluster-center distances in the K-means algorithm. Moreover, since the 1st-level K-means are independent from each other, distributed computing methods can be applied to further reduce the computation time. The numerical analysis can be referred to in Section 7.1.

Another advantage of bottom-up K-means clustering resides in the system update and scalability. In the case of new genre videos added to the dataset, a codebook update module is applied to find the new genre's individual codebook. The result, together with existing codebooks, is used to generate the new generic codebook by only rerunning the 2nd-level K-means. In the case that new videos are imported for an existing genre, the corresponding 1st-level K-means is applied to achieve the updated individual codebook, and then 2nd-level K-means is rerun to update the generic codebook.

At the next step, training data is characterized by frequency-based histogram representation. The individual genre is modularized as a distribution denoted by P using training data of its own kind.

4.3. Genre Categorization

In the final genre categorization stage, a query video is expressed as a histogram Q that also uses the generic codebook and BoW model. Then, a k-Nearest Neighbor (k-NN) classifier is applied with a defined dissimilarity measurement between the query Q and a trained individual genre P. Consequently, the query video is identified as the genre whose distribution is closest to that of the query within measure. Technical details are presented in Section 7.1.

By identifying the genre of this query video, subsequent processes are confined to a focused group, and the scale of computation is decreased. Therefore, advanced and sophisticated techniques can be used in middle/high-level video analysis.

5. MIDDLE-LEVEL VIEW TYPES CLASSIFICATION

This section introduces the middle-level view classification in which the previously built BoW model is also used in feature representation of view types. As this work targets large-scale videos, an unsupervised-based solution is more applicable and realistic. Therefore, unsupervised probabilistic latent semantic analysis (PLSA)-based models are our focus. PLSA has demonstrated promising results in analyzing cooccurrence data of words and documents in text retrieval [Hofmann 2000]. From a matrix factorization point of view, PLSA belongs to a subgroup called nonnegative matrix factorization, where the factorized matrices are nonnegative [Hofmann 1999]. Because the codebook paradigm with codewords is adopted in mapping visual features to a probability-based histogram which has to be nonnegative, PLSA becomes a more suitable selection compared to other factorization techniques, such as singular value decomposition or principle component analysis.

PLSA relies on the likelihood function of multinomial sampling and aims at an explicit maximization of the predictive power of the model. Incorporating the PLSA plate notation in Figure 3 with the view classification application, the observed state w is defined as codewords with a total predefined codebook of size M. An individual video frame is denoted by d with a total number of training frames N. The latent state z is the view type and the parameter K is the total number of view classes, and in this work, K equals four. The likelihood function is given in Equation (1). The probabilistic distribution is defined as $p(w_i|d_j)$, where w_i is an individual codeword, and d_j is a training frame. Such distribution can be represented by a sum-of-product of two distributions, $p(w_i|z_k)$ and $p(z_k|d_j)$. The former is interpreted as an impact on codewords by a view type, while the latter is the probability of a particular view type given a training frame. The number counted of codeword w_i appearing in a frame d_j is denoted as $n(w_i, d_j)$. The argument of maximum posterior (MAP) estimate z^* is optimized by using an expectation maximization (EM) as shown in Equation (2).

$$\begin{aligned} L &= \prod_{i=1}^{M}\prod_{j=1}^{N} p(w_i|d_j)^{n(w_i,d_j)} \\ &= \prod_{i=1}^{M}\prod_{j=1}^{N}\left(\sum_{k=1}^{K} p(w_i|z_k)p(z_k|d_j)\right)^{n(w_i,d_j)}. \end{aligned} \tag{1}$$

$$z^* = \arg\max_{z} p(z|d). \tag{2}$$

Since SVMs have demonstrated great performance in the field of classification, it is adopted in our view-classification task for comparison purposes. In general, supervised models tend to yield better results but require predefined knowledge. A typical radial

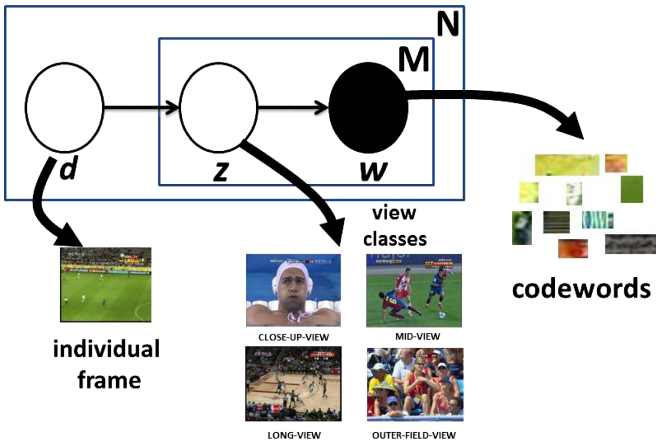


Fig. 3. PLSA model in plate notation is used in view type classification. Parameter z is the latent state, with a total of $K = 4$ view classes, defined as {closed-up-view, mid-view, long-view, and outer-field-view}. d is the individual frame. w is the codeword. The two predefined constants M and N are the codebook size and the total number of training frames, respectively.

basis function (RBF) is used as the nonlinear kernel in SVM [Chang and Lin 2001] and shown in Equation (3). In this equation, x_i and x_j represent the codewords, and γ is the kernel parameter of the RBF.

$$K(x_i, x_j) = \exp\left(-\gamma \left\|x_i - x_j\right\|^2\right), \quad \gamma > 0. \tag{3}$$

Four view types are defined, namely close-up-view, mid-view, long-view, and outer-field-view. This definition is also popular among other works in this field [Xu et al. 2001; Ekin and Tekalp 2002; Duan et al. 2003]. For the PLSA-based model, the number of view types is required in terms of human effort, and no labeling is required for individual frames. On the contrary, SVM-based models demands both semantic predefined view types as well as all frames labeled with ground truth, which could be unaffordable when the video is large-scale in size.

As the result of the view-classification task, the query video sequence is labeled with view types. In the next section, models which take labeled video sequence as input for detecting interesting events are introduced.

6. HIGH-LEVEL EVENT DETECTION

Content-based video event detection is among the most popular quest for high-level semantic analysis. Different from video abstraction and summarization which target any interesting events happening in a video rush, event detection is only constrained to a predefined request type, such as the third goal or the second penalty kick in a particular soccer match. In sports videos, a consumer's interest in events resides in the actual video contents, more than just the information delivered. For instance, a user wants to watch particular goals in basketball games or replays in soccer matches. S/he is not only interested in information like who/how/what was scored, but more importantly, the visual contents rendered from the sports clip. On the other hand, sports videos also have very strongly correlated temporal structures. In a way, such structure can be interpreted as a sequence of video frames which have patterns and internal connections. The existence of these pattern is ubiquitous due to the nature of sports, that is, a competition where players learn from the standard in order to excel. Therefore, an intuitive approach is to find such patterns using certain representations and to learn the temporal structure. Luckily, the PLSA approach provides such a

labeled frame sequence, and what we need is a clever technique by which to analyze portions of the video and determine what robust structured prediction model to use. Following, we will introduce a coarse-to-fine scheme and hidden conditional random field (HCRF) for event detection.

6.1. Event Detection Using Coarse-to-Fine Scheme

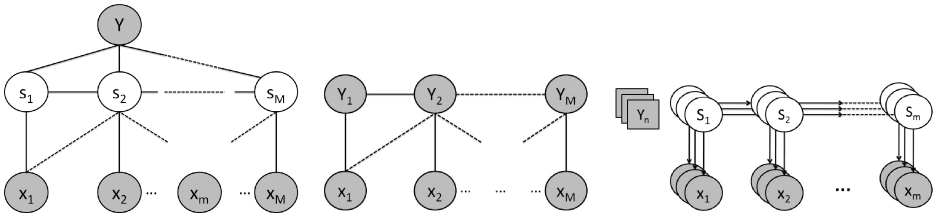
Before learning the tempo and patterns, a starting and entry point of an event needs to be seized. A two-stage coarse-to-fine event detection strategy is suitable for this scenario. The first stage is a rough event recognition and localization utilizing rich and accurate text-based information either from webcasting text or optical character recognition (OCR) techniques of the scoreboard update. In the second stage, precise video contents associated with the semantic event have been detected in terms of event boundary detection and accuracy analysis.

The coarse-to-fine techniques have been proven effective and accurate from our previous works. Webcasting text for coarse-stage event detection and video alignment was studied and analyzed, such as replaying scenes and various goal and shot scenes detection in soccer videos [Dai et al. 2005; Xu et al. 2006]. At the coarse stage, we captured the text event by extracting keywords from either the well-structured or freestyle webcasting text. Then, the extracted text event provided a timestamp for the visual event entry point. At the second fine stage, our previous work continued to rely on webcasting textual information such as text/video alignment, and on accurate information match, such as the detailed process of the event, including players' involvement in the event [Xu et al. 2006]. Since the experiment conducted in this work focuses on fine-stage process with basketball data, we won't repeat the previous work using webcasting text for video analysis. The previously mentioned related works can be referred to in detail for those who are interested.

6.2. Hidden Conditional Random Field (HCRF) Model

In this article, since the proposed framework targets the generic learning model that can be extended to large scale, we rely on the visual contents, that is, the local features extracted and middle-level views classified from such features. To demonstrate the effectiveness of the proposed model , we focus on a particular basketball score event detection. We adopted the previously developed scoreboard update detection method for a coarse-stage process in order to obtain the timestamp [Miao et al. 2007]. The fine-stage process focuses on a robust and accurate visual content detection from the score event. The video sequence is analyzed by distinguishing the actual score event from false alarm events, such as timeouts or intermissions, which are also concurrent with scoreboard information. We propose a HCRF-based structured prediction model utilizing previously classified views, thereby completing the generic approach. For example, the HCRF model can be used to detect the score event in basketball for exciting events and highlights. Such an HCRF technique belongs to the state event model defined in related works. Therefore, the HCRF takes the labeled sequences as input in a natural and seamless fashion. On the other hand, the HCRF is a comprehensive model which can be degraded to hidden Markov models (HMM) or conditional random fields (CRF) with certain constraints. The merits of HCRF compared with the other two models are its resilience and robustness with a combination of both the hidden states and the Markov property relaxation. Technical details are examined in the following.

There are several advantages of using the HCRF in large-scale datasets, rather than HMM or CRF models. First, HCRF relaxes the Markov property, which assumes that the future state only depends on the current state. In our generic framework, video frames are uniformly decimated and sampled, regardless of the temporal pace



(a) HCRF (b) CRF (c) HMM

Fig. 4. Structured prediction models: (a) hidden conditional random field (HCRF); (b) conditional random field (CRF); (c) hidden Markov model (HMM).

of the video itself. In some cases, several consecutive frames have the same labeling, while in other cases, different labels are assigned. Markov property-based models such as HMM are appropriate for the former scenarios but not suitable for the latter ones, since the future state in HMM only cares about the current state label, not previous states. On the other hand, HCRF is flexible and takes surrounding states from both before and after the current state. Thus, HCRF is more robust for dealing with large-scale homogeneous processes and uniform sampling with no prior knowledge. For instance, if a key frame immediately preceding the current state is missed due to uniform sampling, such information loss could be compensated by including and summing up distant informational frames (both previous and future) from uniform sampling without misclassifying the event.

Second, HCRF has merit in its hidden states structure, which helps to relax the requirement of explicit observed states. This is also an advantage in dealing with large-scale uniformly sampled video frames, because in computation, the CRF model outputs individual result labels (such as event or not event) per state and requires separate CRFs to present each possible event [Xu et al. 2008]. In HCRF, only one final result is presented in terms of multiclass events occurring probabilities. From the robustness point of view, a CRF model can be easily ruined by semantically unrelated frames due to automatic uniform sampling. A multiclass HCRF, on the other hand, can correct the error introduced by such unrelated frames using probability-based outputs [Quattoni et al. 2007].

Moreover, HCRF is also appealing in allowing the use of not explicitly labeled training data with partial structure [Quattoni et al. 2007]. From literature, HCRF has been successfully used in gesture recognition [Wang et al. 2006; Quattoni et al. 2007] and phone classification [Gunawardana et al. 2005].

Figure 4(a) illustrates an HCRF structure in which a label $y \in Y$ of event type is predicted from an input $\mathbf{X}$. This input consists of a sequence of vectors $\mathbf{X} = \mathbf{x}_1, \mathbf{x}_2, ..., \mathbf{x}_m, ..., \mathbf{x}_M$, with each $\mathbf{x}_m$ representing a local state observation along the HCRF structure. In order to predict y from a given input $\mathbf{X}$, a conditional probabilistic model defined in Quattoni et al. [2007] and in Equation (4) is adopted. In the equation, model parameter θ is used to describe the local potential function ψ, which is expanded in Equation (6). A sequence of latent variables $\mathbf{h} = h_1, h_2, ..., h_m, ..., h_M$ are also introduced in Equation (4), which are not observable from the structure of Figure 4(a). Each h_m member of $\mathbf{h}$ corresponds to a state of s_m. The denominator $Z(\mathbf{X}; \theta)$ is the normalization factor, which is expanded in Equation (5).

$$P(y|\mathbf{X}, \theta) = \sum_{\mathbf{h}} P(y, \mathbf{h}|\mathbf{X}, \theta) = \frac{\sum_{\mathbf{h}} e^{\psi(y, \mathbf{h}, \mathbf{X}; \theta)}}{Z(\mathbf{X}; \theta).} \tag{4}$$

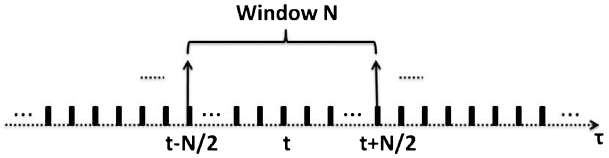


Fig. 5. HCRF input shown in Equation (7) by sliding window average result on view types of decoded image sequence.

$$Z(\mathbf{X};\theta) = \sum_{y',\mathbf{h}} e^{\psi\left(y',\mathbf{h},\mathbf{X};\theta\right)}. \tag{5}$$

$$\psi(y,\mathbf{h},\mathbf{X};\theta) = \sum_t \sum_k \theta_k^1 f_k^1(y,h_t,\mathbf{X}) + \sum_t \sum_k \theta_k^2 f_k^2(y,h_{t-1},h_t,\mathbf{X}). \tag{6}$$

In the event detection application, each $\mathbf{x}_m$ from $\mathbf{X}$ is a vector descriptor called local observation. In the notation, the $\mathbf{x}_m$ value at a time t is defined as $\mathbf{x}_m(t) = [p_{ws_1}(t), p_{ws_2}(t), p_{ws_3}(t), p_{ws_4}(t), p_{wc}(t)]$, with each entry of $\mathbf{x}_m(t)$ calculated from an average result of a sliding window centering at time t, as Figure 5 shows. The first four entries of $\mathbf{x}_m(t)$ are the probabilities of four possible view types, where $p_{ws_{j=1,2,3,4}}(t)$ associates with close-up-view, mid-view, long-view, and outer-field-view by $j = 1, 2, 3, 4$, respectively. The fifth $p_{wc}(t)$ value is an associated directional motion descriptor introduced by Tan et al. [2000]. The formula to calculate the average values at timestamp t are given in Equation (7), where individual frame based probabilities are $p_{s_{j=1,2,3,4}}$ and p_c.

$$\begin{aligned} p_{ws_j}(t) &= \frac{1}{N}\sum_{\tau=t-N/2}^{t+N/2} p_{s_j}(\tau) \quad with \;\; j = 1,2,3,4. \\ p_{wc}(t) &= \frac{1}{N}\sum_{\tau=t-N/2}^{t+N/2} p_c(\tau). \end{aligned} \tag{7}$$

A label and training sequence pair is defined as $(y_i, \mathbf{X}_i)$ with the index number $i = 1, 2, ..., n$. For each pair, $y_i \in Y$ and $\mathbf{X}_i = \mathbf{x}_{i,1}, \mathbf{x}_{i,2}, \mathbf{x}_{i,m}, ..., \mathbf{x}_{i,M}$ are the event label and observed states as Figure 4(a) depicts. For instance, $\mathbf{x}_{i,m}$ is interpreted as the mth sampled time state of the ith training sequence, where $\mathbf{x}_{i,m}(t) = [p_{i,ws_1}(t), p_{i,ws_2}(t), p_{i,ws_3}(t), p_{i,ws_4}(t), p_{i,wc}(t)]$.

During HCRF training, parameters θ_k^1 and θ_k^2 need to be learned. As Equation (6) shows, θ_k^1 and θ_k^2 are coefficients for the state feature function f_k^1 which only involves a single hidden state, and the transition feature function f_k^2 involving two adjacent hidden states, respectively. In order to find the optimal parameters, a log-likelihood objective function is used, as shown in Equation (8), with a second term called shrinkage prior to avoid the parameters getting too large. A limited-memory version of the Broyden-Fletcher-Goldfarb-Shanno (L-BFGS) quasi-Newton gradient ascent method [Morency et al. 2008] is applied to find the optimal $\theta^* = argmax£(\theta)$. The L-BFGS algorithm is chosen due to this method's efficiency and performance from both theory [Sha and Pereira 2003] and application [Xu et al. 2008].

In the optimization process, the conditional probability in Equation (8) is substituted by the explicit form in Equation (4) to get Equation (9). Then, partial derivatives

of a training sample $\pounds_i(\theta)$ with respect to θ_k^1 and θ_k^2 are derived in Equations (10) and (11), respectively.

$$\pounds(\theta) = \sum_i \log p(y_i|\mathbf{X}_i, \theta) - \frac{1}{2\delta^2}\|\theta\|^2. \tag{8}$$

$$\pounds(\theta) = \sum_i \log\left(\frac{1}{Z(\mathbf{X}_i;\theta)}\sum_{\mathbf{h}} e^{\psi(y_i,\mathbf{h},\mathbf{X}_i;\theta)}\right) - \frac{1}{2\delta^2}\|\theta\|^2. \tag{9}$$

$$\begin{aligned}\frac{\partial \pounds_i(\theta)}{\partial \theta_k^1} &= \sum_t P(h_t|y_i,\mathbf{X}_i) f_k^1(y_i,h_t,\mathbf{X}_i) \\ &\quad - \sum_{t,y'} P(h_t,y'|\mathbf{X}_i) f_k^1(y',h_t,\mathbf{X}_i).\end{aligned} \tag{10}$$

$$\begin{aligned}\frac{\partial \pounds_i(\theta)}{\partial \theta_k^2} &= \sum_t P(h_{t-1},h_t|y_i,\mathbf{X}_i) f_k^2(y_i,h_{t-1},h_t,\mathbf{X}_i) \\ &\quad - \sum_{t,y'} P(h_{t-1},h_t,y'|\mathbf{X}_i) f_k^2(y',h_{t-1},h_t,\mathbf{X}_i).\end{aligned} \tag{11}$$

6.3. Connection with Conditional Random Field (CRF) and Hidden Markov Model (HMM)

For comparison purposes, we also utilized a conventional CRF model, as depicted in Figure 4(a). By following definitions in Lafferty et al. [2001], the conditional probability function is shown in Equation (12), with the normalization factor in Equation (13). The potential function is defined in Equation (14), where $v_j(Y_{t-1}, Y_t, \mathbf{x})$ is a transition feature function between state positions t and $t-1$ with the entire observation sequence; while $s_k(Y_t, \mathbf{x})$ is a state feature function at state position t. λ_j and μ_k are parameters to be estimated for transition and state feature functions, respectively.

$$P(\mathbf{Y}|\mathbf{x}) = \frac{1}{Z(\mathbf{x})} \cdot exp\left(\sum_{t=1} F(\mathbf{Y}, x, t)\right). \tag{12}$$

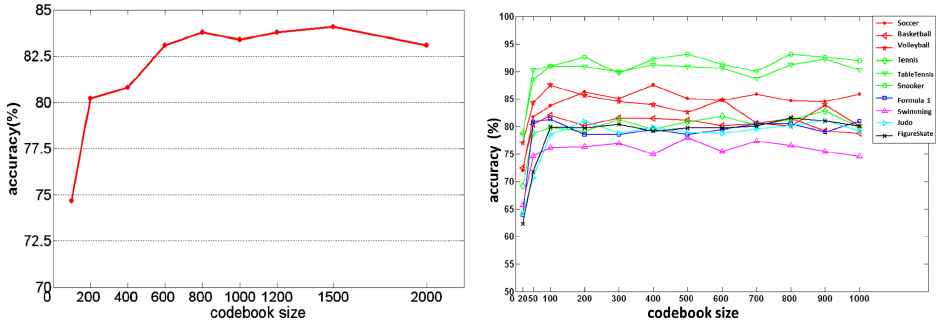
$$Z(\mathbf{x}) = \sum_{Y'} exp\left(\sum_{t=1} F(Y', \mathbf{x}, t)\right). \tag{13}$$

$$F(Y, \mathbf{x}, t) = \sum_j \lambda_j v_j(Y_{t-1}, Y_t, \mathbf{x}) + \sum_k \mu_k s_k(Y_t, \mathbf{x}). \tag{14}$$

The HMM algorithm is also provided in Equation (15) and depicted in Figure 4(c).

$$\begin{aligned}P(Y|X) &= P(X,Y)/P(X) \\ &= \prod_t P(X_t|Y_t) \cdot P(Y_t|Y_{t-1}).\end{aligned} \tag{15}$$

Different methods are used for detecting an event in the decision stage of the aforementioned three structured prediction models. For the HMM, the query sequence will be tested, and the highest likelihood of the HMM provides the final decision in event detection. On the other hand in the CRF model, since each state variable $Y(t)$ requires a label, as Figure 4(b) shows, a majority-rule voting scheme in which the most event



(a) (b)

Fig. 6. Empirical studies on codebook size selection. (a) Average sports accuracy performance for genre categorization with sports listed in the column plot 0**??**. (b) Individual sport accuracy performance for view classification.

labels along the Y sequence decide the event result. For the HCRF model depicted in Figure 4(a), a multiclass training process recognizing all classes at the same time is adopted. Therefore, a detected event with the highest probability is considered the final result for the query sequence.

7. EXPERIMENTS AND RESULTS

In the following, experimental results are presented to justify the properties of the proposed generic framework, specifically using a relatively large-scale video collection that includes 23 genres with a total of 145 hours gathered by the authors named the 23-sports dataset. To our best knowledge, this dataset is the most diverse in video genres, collected from both Internet and TV recordings. All the video clips have the same length of 167 seconds with a total of 500 uniformly sampled frames at a sampling rate of three frames per second. This dataset is composed of 3,122 clips. In training, 1,198 clips are used, in which a subset of 46 clips (2 clips per sport) are used in codebook generation with a total of 3,112,341 SIFT points. In testing, the other 1,924 clips are selected.

Various codebook sizes are studied at first. Then the proposed system is evaluated by three experiments with a particular event detection as its ultimate measurement: (1) genre categorization using the proposed bottom-up codebook generation is analyzed; (2) view classification results are assessed and compared using both supervised and unsupervised classifiers; (3) finally, the coarse-to-fine event detection is examined by investigating the basketball score event. The validity on the score event detection can be extended to other event scenarios with labeled video sequences. The detailed argument can be found in Section 7.3.

To investigate the codebook size effectiveness, a subset of the 23-sports dataset of 14 sports is used. The clip numbers of these sports range from 70 to 106 at an average of 87, while each individual clip is a uniform 167 seconds in length. Two experiments are conducted on the codebook size selection for genre categorization and view classification, respectively. For genre categorization, the average accuracy performance of all sports as a function of different codebook sizes is shown in Figure 6(a). The plot plateaus after codebook size 800 and starts to drop at 1,500. For view classification, the accuracies of individual sports as a function of different codebook sizes are shown in Figure 6(b). Although various accuracy levels are observed for each sport, the individual performance follows a similar plateau trend. Based on these empirical studies, it is concluded that the performances are proportional to codebook sizes, with stable results at codeword ranges of 800–1500 and 800–1000 for genre categorization and

Table IV. SSE Deviation Percentage δ_{dev} and Computation Time in Codebook Generation Using Bottom-Up and Single K-Means Structures

Codebook Size	cb_{BU} =800	cb_{SK} =800	cb_{BU} =1600	cb_{SK} =1600
δ_{dev}	1.4 %		3.7 %	
Computation	4hrs	350hrs	9hrs	648hrs

view classification, respectively. This study is also consistent with existing research [Jiang et al. 2010; Philbin et al. 2007; Yang et al. 2007]. In the following experimentation for genre categorization with a total of 23 sports types, it is predicted that the codebook size should be bigger than in the tested 14 sports case. Therefore, a codebook size of 1,600 is chosen, and a codebook size of 800 is also applied as comparison analysis. For view classification involving 14 sports, a codebook size of 800 is selected.

7.1. Genre Categorization Using a k-Nearest Neighbor (k-NN) Classifier

In genre categorization, a k-nearest neighbor (k-NN) classifier is applied. Three different dissimilarity measurements are compared, including Euclidian distance (ED), earth mover's distance (EMD), and Kullback-Leibler divergence (KL-div). ED is used for measuring the spatial distance in Euclidian space in between two histograms. EMD is a distance function for achieving the minimal cost in transforming one histogram into the other [Rubner et al. 2000]. The KL-div is a non-symmetric measurement between two probability distributions Q and P defined as $D_{KL}(Q||P) = \sum_i q_i \cdot \ln(q_i/p_i)$ [Duda et al. 2001]. In this work, q_i and p_i are individual codewords for the query video Q and the trained genre model P, respectively.

Before accuracy performance analysis on genre categorization, codebook generation schemes are examined by comparing both the proposed two-level bottom-up (BU) structure and the baseline single K-means (SK) clustering method. As pointed out by Jain et al. [1999], K-means clustering is considered a partitional algorithm using the squared error to reach the optimum solution. The sum of squared errors (SSE) is a widely used criterion function for clustering analysis, which quantitatively measures the total difference between all individual points to their clustering centers [Duda et al. 2001]. An SSE deviation percentage δ_{dev} is defined in Equation (16). Let ξ_{BU} and ξ_{SK} represent the SSEs of the bottom-up-based clustering and the single K-means clustering at the end of each algorithm, respectively. The numerator is the absolute value of the difference between ξ_{BU} and ξ_{SK}, and the denominator is ξ_{SK}. As Table IV shows, the SSE deviation percentages at codebook sizes of 800 and 1,600 are 1.4% and 3.7%, respectively. Thus, we can conclude that in using the bottom-up structure instead of the single K-means clustering for codebook generation, the deviation of SSE is trivial.

$$\delta_{dev} = \frac{|\ \xi_{BU} - \xi_{SK}\ |}{\xi_{SK}} \cdot 100\%. \tag{16}$$

Codebook computation effort of the bottom-up structure is also compared with single K-means clustering in Table IV. Both bottom-up and single K-means clustering are employed on a single Quad CPU at 2.40GHz with 4.0G RAM machine, in which the bottom-up is only simulated as parallel computing in a serial sequence. To generate a codebook with size 800, the single K-means clustering uses 350 hours, while the bottom-up-based clustering only takes four hours. When the codebook size is doubled to 1,600, the computations for single K-means- and bottom-up-based clustering are 648 hours and 9 hours, respectively. With a truly distributed processing environment using multiple computers, bottom-up-based processing time will be further reduced. This

Table V. Average Categorization Results (%) of 23-Sports Data with Codebook Size 800 and 1,600

Measurement	ED	EMD	KL–div
$\mathbf{cb_{BU}}$**=800**	61.54	75.80	78.59
$\mathbf{cb_{SK}}$**=800**	68.31	75.33	73.49
$\mathbf{cb_{BU}}$**=1600**	65.68	78.94	82.16
$\mathbf{cb_{SK}}$**=1600**	65.39	64.28	75.75

Note: BU: codebook generated using bottom-up structure. SK: codebook generated using single K-means structure.

demonstrates that our generic framework using robust bottom-up-based clustering for codebook generation can replace the single K-means in dealing with large-scale and diverse datasets.

For the accuracy performance using k-NN and various dissimilarities, Table V shows the average genre categorization results for 23 different sports. The proposed bottom-up codebook generation manifests a better and more robust performance than single K-means codebook generation in both EMD and KL-div measurements. By comparing the row-wise various dissimilarities, the bottom-up structure is more consistent with codebook sizes of 800 and 1,600. On the contrary, the single K-means-based codebook generation is unstable for both histogram and mLDA-based distributions. For instance, the performance at a codebook size of 800 using EMD has about a 7% increment from ED dissimilarity (75.33% vs. 68.31%), while the counterpart at a codebook size of 1,600 using EMD has dropped 1.1% from ED dissimilarity (64.28% vs. 65.39%). One reason is that the single K-means clustering on over 3 million input SIFT points hardly reaches the optimal value. As a summary, KL-div performs the best among three dissimilarity measures. Using the bottom-up structure, results of the codebook size 1,600 outperform the cases with size 800 in all measurements with consistency. Oppositely, single K-means clustering results are not consistent.

Another merit of the bottom-up structure is its preservation of individual genre characteristics from the 1st-level K-means. On the contrary, single K-means codebook generation covers all the data; thus, a weakly distinguishable genre is easily overruled by a strong one. This explains why with the increase of codebook size from 800 to 1,600, the bottom-up process has about 4% improvement for KL-div, while the single K-means process has only a 2% increment for KL-div.

The individual sport genre classification result is illustrated in Figure 7. On average, a codebook size of 1,600 gives an average of 3.6% higher than the codebook size of 800, which agrees with the empirical studies from other research groups [Jiang et al. 2010; Yang et al. 2007].

To evaluate the generic and extensive properties of our proposed approach, experiment results on the 23-sports dataset are compared with results in Li et al.'s work [Li et al. 2009], where a top-down process was used with single K-means as its top layer general codebook. The best performance in two-layer and single-layer structures are 83.83% and 81.2%, respectively [Li et al. 2009]. In their work, a speeded up robust features (SURF)-based method is adopted. Similar to SIFT, SURF is also a scale and rotation-invariant interesting point feature extraction algorithm, which focuses on the computational efficiency [Bay et al. 2006]. Although SURF and SIFT adopt different key points detection techniques, these two descriptors are comparable in characterizing local features of sampled frames from a video sequence. Therefore, such a comparison is valid in genre categorization performances, regardless of the feature extraction difference. Considering the increment of data in scale is about 27% (145 hrs vs. 114.2 hrs), while in diversity is about 64% (23 genres vs. 14 genres), using the

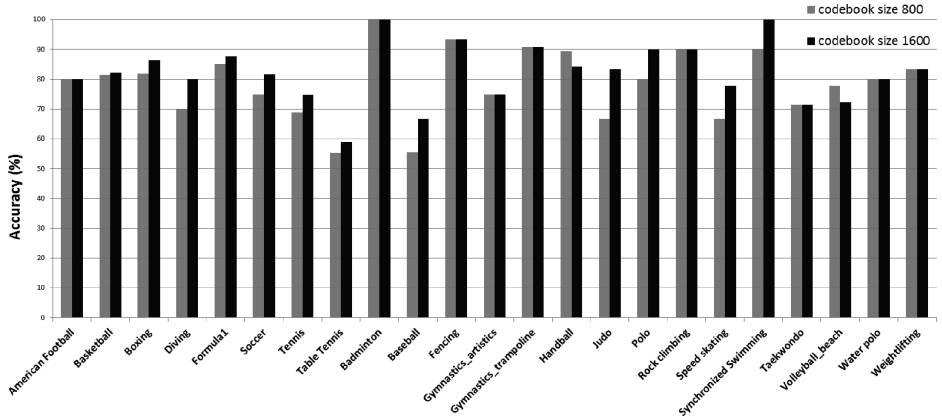


Fig. 7. Genre categorization for the 23-sports dataset with codebook sizes of 800 and 1,600.

Table VI. Genre Categorization Accuracy between Various Video Clips with Uniform Sampling-Based and Key Frame/Shot-Based Methods

3 Minutes Clip		*10 Seconds Clip*	
Uniform Sampling	**Key frame/ Shot**	**Uniform Sampling**	**Key frame/ Shot**
83.83%	79.41%	71.90%	63.10%

bottom-up structure with a codebook size of 1,600 and KL-div measurement, our experimentation provides comparable results of 82.16%, with a degradation of 1.67%.

Although the performance is maintained averagely, we also observed that the individual performance has been fluctuant. This is mainly due to the nature of the adopted k-NN classifier, where distance-based measurement can be overruled by a strong representation in a large and sparse dataset. We acknowledge that k-NN may not be the most robust approach towards the very large-scale dataset. However, k-NN is an efficient method in batch processing. It can be used as a coarse and preliminary execution to quickly prune off the large portion of the irrelevant data.

From a different perspective, generic property of the proposed approach is assessed using various video clip lengths and frame sampling methods. As detailed in Table VI, better performance is acquired using longer length of video clips, while a generic and automatic uniform sampling method outperforms the key frame-based sampling. This is because the proposed approach is based on local key-point descriptors. Therefore, a longer video clip with denser sampling frames provides more key-points and consequently builds a better distribution than a shorter clip with less sampled key frames/shots. Such experimentation demonstrates the merit of our proposed generic approach toward a truly large-scale dataset.

7.2. View Classification Analysis Using Supervised SVM and Unsupervised PLSA

Experiments in this section focus on middle-level view classification by utilizing extracted low-level histogram-based representations. A subset of 14 sports of all 23 sports was used as test data which is detailed in the column plot 0**??**. Figure 8 compares both supervised SVM and unsupervised PLSA results as the 1st and 2nd columns, respectively. On average, supervised SVM has a classification accuracy

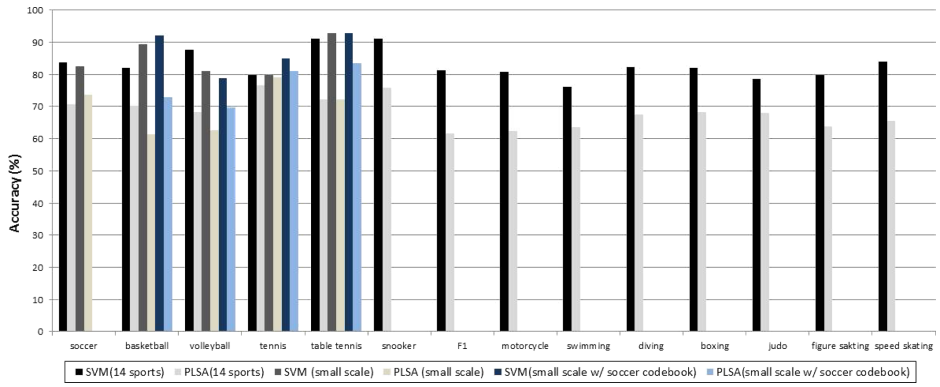


Fig. 8. View type classification using supervised SVM and unsupervised PLSA. First two columns are with codebook size 800 for 14 sports. 3rd and 4th columns are SVM and PLSA performances of a smaller group with five sports {soccer, basketball, volleyball, table tennis, and tennis}. 5th and 6th columns are the SVM and PLSA performances of these 5 sports excluding the soccer sport. The difference between the 5th/6th from 3rd/4th data is that the generated codebook is borrowed from the abundant soccer sport.

of 82.86%, and unsupervised PLSA has an average of 68.13%, in which the SVM technique outperforms the PLSA approach by 14.73%.

It needs to be pointed that this evaluation is based on the predetermined semantic view types, which is in favor of the SVM approach in nature. This is because such a semantic definition has become considerably involved in SVM training, while barely being used in PLSA training. In the SVM method, labeled training data associated with each predefined view type are indispensable for building the classifier. On the other hand, the PLSA model training merely requires a specified number of view types, which is similar to the number of clusters needed for training a K-means clustering. Thus it is anticipated that the supervised SVM method has better performance than the unsupervised PLSA algorithm.

However, the PLSA model is advanced in its unsupervised characteristics such that the labeled data is avoidable in training. This feature makes the PLSA more suitable than the SVM and significant in supporting the generic framework dealing with large-scale datasets, where automatic processes and minimum human and expertise interventions are essential. For evaluating our proposed framework, a trade-off in the classification accuracy can be afforded, if the ultimate event detection results are comparable using either the PLSA or the SVM view results.

In order to analyze the generic and scalable property, a subset with small-scale five-sport dataset is applied, including {soccer, basketball, volleyball, table tennis, tennis}. The SVM and PLSA view classification performance of this small-scale dataset is presented in the 3rd/4th columns of Figure 8, respectively. Baseline with the small-scale data, the 14-sports has a 0.27% performance drop in SVM and an improvement of 1.76% in PLSA . With similar results, compared with the five-sport small-scale data, the 14-sport view dataset has a lot more data in both variety and volume.

Based on the precedings analytical results, the extrapolated performance from this current relatively large-scale dataset to a truly large-scale dataset should maintained, especially for the PLSA method. The reasoning is twofold. First, large-scale data is normally sparse; PLSA, as a generative model, has a characteristics in probabilistically mapping data from a high-dimensional space to a low-dimensional space. Hence more information brought by the new data can help in finding significant representatives in the lower dimensional space. Second, since the number of view classes are fixed at four types, more variety and volume won't affect the performance much.

Table VII. Precision and Recall Results of Basketball Score Events Detection at the First (Coarse) Stage

Correctly Detected Score (true positive)	Detected Score (correct result)	Correct Total Score (obtained result)	Precision (%)	Recall (%)
231	251	268	92.03	86.19

Additionally, a knowledge transfer property is investigated by using the same five-sport dataset. It can be seen that an individual sport from insufficient resources {basketball, volleyball, table tennis, tennis} can be assisted by borrowing the codebook from an abundant sport resource {soccer}. As Figure 8 depicts on these limited-source four sports in the 5th/6th columns, the codebook transfer mechanism has improved about 2.07 % and 5.05% for the SVM and PLSA on average, respectively. The margin of improvement using the PLSA is bigger than its counterpart in the SVM. This can be explained by the nature of two different techniques. PLSA is a probabilistic-based dimensional reduction technique. Therefore, more data will provide a more thorough characterization of the low-dimensional model. On the contrary, SVM is a technique mapping from a low-dimensional space to a higher dimensional space. More information brought by the codebook may be overwhelmed by the SVM process and may not necessarily provide a better classification in the higher dimensional space. Therefore, such a knowledge transfer property could help the unsupervised PLSA in further improving its performance for sports of scarce resources.

7.3. Basketball Score Event Detection Using Coarse-to-Fine Scheme and HCRF-Based Structured Prediction Model

In previous experiments, the proposed framework provides an application to identify video genres by directly utilizing domain knowledge-free SIFT descriptors and a BoW model. After the genre is determined, individual frames of the query video sequence are labeled by the middle-level semantic views via either supervised or unsupervised classifiers. In this experiment, the task on basketball score event detection is investigated by employing this labeled video sequence. A two-staged coarse-to-fine scheme is adopted that first detects scoreboard information change, introduced by Miao et al. [2007]. By adopting this technique, an entry point of an interesting event is located. However, this coarse detection only provides a static frame-based rough estimation as an entry point. Since scoreboard information not only appears in score events but also in time-out events or intermission events, individual frame-based detection without temporal structured information cannot provide robust and satisfactory results. Therefore, a fine tuning process in finalizing detection is adopted to ensure that the query video truly conveys the score event as its semantic theme. The proposed HCRF model is deployed as such a process after the first-stage coarse detection. Experimental results using this HCRF model are compared with CRF and HMM baselines.

Two video groups consisting of four matches are utilized, which are defined as (a) Dataset A: using two NBA games for training and using another two Olympic Games for testing; (b) Database B: using one NBA game for training and using another NBA game for testing. Frame-based views from the PLSA model and the SVM model are applied to Dataset A and B. Therefore, four combinations of view labels and datasets are defined as $PLSA + A$, $PLSA + B$, $SVM + A$, and $SVM + B$. Each video clip used in both training and testing is automatically decimated and consists of 500 uniformly sampled frames. We use a window size $N = 20$, which is introduced in Figure 5 and Equation (7) from Section 6, with a window N sliding every ten frames. The final number of the states sequence for HCRF is thus calculated as $49 = 500/(20 - 10) - 1$.

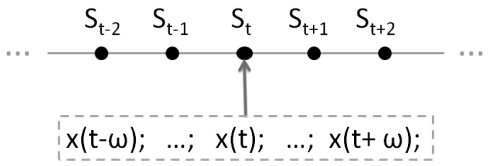


Fig. 9. Current state influenced by surrounding observed states.

Table VIII. Performance Comparison on Score Event Detection in Basketball

	Accuracy			
	Dataset A (NBA/Olympics)		**Dataset B (NBA/NBA)**	
	SVM+A (%)	PLSA+A (%)	SVM+B (%)	PLSA+B (%)
HMM $\omega = 0$	78.28	75.29	87.50	85.94
CRF $\omega = 0$	78.16	74.57	87.43	86.52
CRF $\omega = 1$	79.52	76.82	88.52	87.89
HCRF $\omega = 0$	80.93	75.53	90.00	90.77
HCRF $\omega = 1$	83.26	80.24	93.08	92.31
HCRF $\omega = 2$	82.09	77.88	91.46	91.77

Note: Dataset A: NBA matches as training, Olympic matches as testing. Dataset B: NBA matches for both training and testing.

The number of approximated events detected after the first stage is given in Table VII. The precision and recall of the coarse-stage basketball score detection are 92.03% and 86.19% respectively. In the second stage, the proposed HCRF-based model and state-of-the-art HMM and CRF models are evaluated and compared. The advantage of HCRF over HMM is its relaxation on the Markov property that the current state S_t can be inferred from both current observations as well as surrounding observations. This is illustrated in Figure 9. In the experiment, the circumferential range number is selected at $\omega = 0, 1, 2$. As shown in Table VIII, the HCRF has better performance than the CRF for the same ω values, while both models outperform the HMM baseline. When using different ω values for both CRF and HCRF, $\omega = 1$ provides better results than $\omega = 0$, in which neighboring information assists in better decision making. However, when $\omega = 2$ is used for HCRF, the performance has been dropped for all cases compared with $\omega = 1$. This can be viewed as an overfitting issue, in which adding more surrounding information limits the structured prediction ability. A similar overfitting problem is also observed in gesture recognition research using HCRF [Quattoni et al. 2007]. In summary, the proposed HCRF-based model with parameter $\omega = 1$ outperforms both CRF and HMM models. The best results are obtained at 93.08% and 92.31% by taking SVM- and PLSA-based input labels, respectively.

On the other hand, by comparing the input of basketball videos, the performance discrepancy of event detection has been shortened, as we compare column-wise SVM with PLSA in both datasets, although the input views after classification shown in Figure 8 has PLSA (70.14%) outperformed by SVM (82.00%) by 11.86%. For Dataset A, the average difference shows that SVM outperforms PLSA by 3.65%, while in Dataset B, such a difference is only 0.47%. This demonstrates the robustness and resilience of structured prediction models in accommodating not well labeled video sequences from PLSA, yet achieving comparable performance as with input from SVM learning. Therefore, the event detection presented in this work achieves similar results by both unsupervised learning and supervised learning approaches. However, due to PLSA's much less human involvement, the unsupervised classifier is preferred in the large-scale video analysis.

Experimental result discrepancies using Dataset A and Dataset B are also compared. Although both datasets belong to basketball, Dataset B using NBA matches for both training and testing outperformed Dataset A with NBA matches for training but Olympics matches for testing, by 10.9% on average. It suggests that albeit datasets A and B are of the same genre and event detection task, a significant difference exists. This can be explained by assuming that NBA and international basketball (FIBA) are two different styles of the same genre. In terms of computer vision and structured prediction, NBA and FIBA have related but different temporal patterns even in the same semantic event. Thus, by training/testing in the same style, it is expected to have a better detection rate, than training/testing using different styles. This is an example of the semantic gap—that semantic event recognition with discrepant conditions is still not perfect.

Although there is only one event detection example discussed in this article, It is believed that the approach can be extended and generalized to a bigger pool of event scenarios. The reason is fourfold. First, the experiment data of the basketball score event are multisource and non-simplex. Videos are collected from both Internet and TV recordings, and there are different production rules of NBA and Olympics basketball. Second, the video representation module using local features and the BoW model is domain knowledge-free with no production rules involved. Such a generic approach has been proven to be effective in genre categorization of 23 sports, view classification of 14 sports, and the basketball score event. Third, the event detection approach utilizing HCRFs as well as baseline HMMs and CRFs structured prediction model and belongs to the category of state event model. By comparing the number of events analyzed using different event models from Table III, the state event model is a popular approach in recent years, with a lot more events handled than the other two model types. In addition, among the state event models, most methods utilize middle-level semantic agents. In our work, the adopted four-category view type definition is one of the most popular classification schemes in literature. Last, and most important, the input of our event detection model is a sequence of labeled views which is the result of a domain knowledge-free method (either PLSA or SVM), using generic video representation. With better accuracy achieved by the proposed HCRF-based model than baselines HMM- and CRF-based models, the performance should be maintained with other labeled sequences which could form various event scenarios. Moreover, utilizing sequences labeled by the middle-level agents as input is also popular among peers' works with state event models [Tong et al. 2004; Wang et al. 2006; Xu et al. 2008; Zhang et al. 2007].

8. CONCLUSION

This article introduces a generic framework for analyzing a relatively large-scale diverse sports video dataset with three video analysis tasks in a coherent and sequential order. By processing all data indifferently at the feature extraction stage using domain knowledge-free local SIFT descriptors, various video data are represented by compact and concise BoW models. Then, a systematic approach is employed for event detection targeting on a query video sequence, which may embody an interesting event. In this approach, after its genres first identified using a k-NN classifier, the query video is evaluated with a semantic view assignment as the second stage with the PLSA model. Both tasks utilize the initially processed video representation as input. Finally, in the third task, the interesting event is detected by feeding the view labels into an HCRF structured prediction model.

Overall, this framework demonstrates the efficiency and generality in processing voluminous data from a relatively large-scale sports collection and achieves various tasks in video analysis. The affectiveness of the framework is justified by extensive

experimentation and results are compared with benchmarks and state-of-the-art algorithms. As a conclusion, with little human expertise and effort involvement in both domain knowledge-independent video representation and annotation-free unsupervised view labeling, the proposed generic and systematic approach is promising in processing sports video datasets, with a potential of being extended to real large-scale and diversified datasets.

Our future work will focus on expanding the current dataset to a dataset truly large-scale in size and various-type in diversity so that the proposed approach can be examined on a more complicated proving ground. We also will conduct more experiments on event scenarios other than the score event, as well as related high-level semantic analysis, such as tactic analysis, automatic broadcast video generation, etc.

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