Extracting Key Segments of Videos for Event Detection by Learning From Web Sources

Hao Song, Xinxiao Wu, Member, IEEE, Wennan Yu, and Yunde Jia, Member, IEEE

Abstract—In this paper, we present a novel approach of extracting the key segments for event detection in unconstrained videos. The key segments are automatically extracted by transferring the knowledge learned from Web images and Web videos to consumer videos. We propose an adaptive latent structural support vector machine model, where the locations of key segments in videos are regarded as latent variables due to the unavailability of the ground truth of key-segment locations in training data. In order to alleviate the time-consuming and labor-expensive manual annotation of huge amounts of training videos, a large number of loosely labeled Web images as well as videos are collected from the Web sources. Additionally, a limited number of labeled consumer videos are utilized to guarantee the precision of the model. Considering the semantic diversity of key segments, we learn a set of concepts as the semantic description of key segments and explore the temporal information of concepts to capture the sequential relations between the segments. The concepts are automatically discovered by using Web images and videos with their associated tags and description sentences. Comprehensive experiments on the Columbia’s consumer video and the TRECVID 2014 Multimedia Event Detection datasets demonstrate that our method outperforms the state-of-the-art methods.

Index Terms—Event detection, key segments, transfer learning, automatic concept discovery.

I. INTRODUCTION

DETECTING complex events in unconstrained videos is an extremely challenging task due to the arbitrariness of consumer videos in computer vision [1], [2]. The complex events are usually composed of various basic actions, objects and scenes [3]–[5]. A single semantic concept such as the event class label is not sufficient to abstract the contents of complex events. Thus, it is essential to employ multiple semantic concepts as the description of events [6]–[8].

Taking the event of “wedding ceremony” for example, it usually consists of the action concepts of “hugging” and “kissing”, the object concept of “wedding dress”, and the scene concept of “church”. The single concept of “kissing” or “hugging” is not able to interpret this event completely. Moreover, in real scenarios, an event video usually lasts for several minutes or even an hour, so there may be irrelevant or redundant information in video which will negatively impact the understanding of events. In this paper, we try to automatically extract the informative segments from consumer videos for event detection. Considering the temporal relations between key segments in a specific event, it is effective to model the temporal constraints between segments for key segment extraction and event detection.

Since the great intra-class variation exists in event videos, a number of videos are required to achieve the promising results by covering all the possible instances of all the event classes [3], [9], [10]. However, manually annotating the training videos is time-consuming and labor-expensive. To alleviate this problem, we propose to explore rich and loosely labeled Web resources as training data for detecting complex events in consumer videos.

This paper presents an adaptive latent structural SVM to extract key segments for event detection by transferring the discriminative model learned by Web resources to consumer videos, in which the locations of key segments in videos are designed as latent variables. A large number of loosely labeled images (from Flickr and Google) and videos (from Youtube) are utilized in the training phase. Additionally, a limited number of labeled consumer videos are also collected to guarantee the precision of the event detection model. A set of semantic concepts is employed to describe the overall content of a specified event video, and each single semantic concept is chosen as the description of each local video segment. Considering the temporal relationship between different segments represented by the concepts, we develop a Temporal Relation Model (TRM) to exploit the temporal relations between the key segments. We also integrate a Segment-Event Interaction Model (SEIM) into the adaptive latent structural SVM model to evaluate the correlations between the key segments and the specified events.

Since the manually defined concept might fail to represent real-world events without the adaptability to different domains [11], [12], we try to discover the concepts automatically by leveraging the tags and description sentences from Web images and videos. We introduce the N adjacent point sample consensus (NAPSAC) [13] to eliminate the noisy images and videos, and then use the hierarchical clustering [14] to generate the last concepts with their associated Web sources by jointly taking account of the similarity of the textual descriptions and the content of their related resource sets. The detailed framework of our method is shown in Fig. 1.
The main contributions of our method are three-fold: (a) We propose a novel framework to simultaneously extract the key segments of videos and classify the high-level events. Each segment is described by a concept which is chosen from the automatically discovered concept pool. (b) We leverage the knowledge learned from Web videos and images to extract the key segments of videos by exploiting their temporal relationship. (c) We combine the NAPSAC and the hierarchical clustering to automatically discover the concepts to extract the segments in videos.

II. RELATED WORK

A. Domain Adaptation for Event Detection

Many researchers draw attention to the topic of detecting complex events in videos using domain adaptation since the limitation number of training examples. Zhang et al. [15] leveraged abundant Web images to learn the noise-resistant classifiers for modeling the event-centric semantic concepts. The concepts are encoded in the knowledge base to narrow the semantic gap between complex events. Wang et al. [16] presented a set of concept groups to incrementally learn the target classifier, where each concept group consists of the images querying from Web and some simple action videos. Long et al. [17] proposed a transfer kernel learning method to learn a domain-invariant kernel by matching source and target distributions in the reproducing kernel Hilbert space. Duan et al. [18] proposed a multiple source domain adaption method by selecting the most relevant image source domains for annotating videos. Different from these methods which encode a global video-level feature over the entire video, our method extracts the local segment-based features for recognizing complex events.

B. Extracting Segments of Videos for Event Detection

Due to the complexity of unconstrained videos, many methods focus exploiting the segments of videos for complex event detection. Phan et al. [3] divided a video into several segments for feature extraction and classification, using the segment-based approach to produce a video representation for event detection. Li et al. [19] detected bursty tweet segments as event segments and clustered the segments into events by considering both the frequency distribution and content similarity of segments. Song et al. [20] detected the key segments of complex videos by leveraging image sets. Sun et al. [5] proposed an
evidence location model to discover the video segments for event classification and recounting. They also leveraged the detected oriented discriminative segments in videos and the descriptions of segments for event detection [21]. Tang et al. [22] automatically discovered discriminative and interesting segments of videos on the variable-duration hidden markov model. Li et al. [23] leveraged a global dynamic pooling structure to model the temporal relations between segments and the event specific videos. The locations of the segments are also treated as hidden information. Chang et al. [24] presented a joint framework which simultaneously detects high-level events and discovers the segments in event videos. An event video is represented as a mid-level concept semantic vector. And all the relationships are built on this concept representations. Different from these segment discovery methods, the concepts in our framework are automatically discovered. Our method introduces a latent structural SVM framework of event detection which utilizes large amounts of loosely labeled Web sources and a few labeled training target videos. Each segment corresponds to one concept, the segment discovery and event detection are processed simultaneously.

C. Collecting Concepts Manually for Event Detection

Many works also try to detect complex events using the concept learning based methods. Mazloom et al. [25] proposed an approximate solution to find a set of informative concepts using cross-entropy optimization and they learned the concept prototypes from a set of relevant frames of Web video examples without any annotations [26]. Merler et al. [27] presented a mid-level semantic representations with 280 relevant concepts which are trained by labeled Web images. Habibian et al. [4] constructed a pool of 1346 concept detectors trained on the ImageNet [28] and TRECVID [29] to create an effective vocabulary for event recognition. Different from the concepts which are manually defined, we present a new algorithm to automatically discover the concepts from loosely labeled Web images with their associated tags.

III. AUTOMATIC CONCEPT DISCOVERY

A. Generation of Preliminary Concept Pool

Owing to the rapid growing of Web sources, we try to utilize the textual descriptions of large Web images and videos for generating the preliminary pool of concepts. Particularly, we query images and videos by using the textual descriptions of specified events as keywords. Both the images and videos, which are respectively collected from the Flickr and Youtube Websites, have their own semantic tags or description sentences. Thus we can adopt the Term Frequency-Inverse Document Frequency (TF-IDF) algorithm [30] to extract the keywords from those textual descriptions of Web images and videos. Finally, the preliminary concept pool is generated by collecting all the extracted keywords and selecting only the original tags of Web sources with high frequency. For each tag/keyword, it corresponds to a few images or videos, and for each Web image/video, it relates to several tags/keywords.

<table>
<thead>
<tr>
<th>Algorithm 1: Pseudo-code of NAPSAC for Eliminating Noisy Web sources.</th>
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<tbody>
<tr>
<td><strong>Input:</strong> FS: Web sources collected from Flickr and Youtube using event textual descriptions at the first stage; SS: Web sources queried from Google and Youtube using the concept descriptions in preliminary concept pool at the second stage.</td>
</tr>
<tr>
<td><strong>Output:</strong> I: refined concept training example sets.</td>
</tr>
<tr>
<td><strong>For each concept x, the related web sources are refined as follows:</strong></td>
</tr>
<tr>
<td>1. <strong>Step 1:</strong> Select an initial web source (image/video) x₁ from source set FSᵣ.</td>
</tr>
<tr>
<td>2. <strong>Step 2:</strong> Find the set of source, SIₓ₁, from the source set SSᵣ which is lying within a hypersphere of radius R centered on x₁.</td>
</tr>
<tr>
<td>3. <strong>Step 3:</strong> If the number of sources in SIₓ₁ is less than the prescriptive size then fail. In our experiment, we set the prescriptive size of images as 50 and videos as 10, respectively. Return to Step 1.</td>
</tr>
<tr>
<td>4. <strong>Step 4:</strong> Select the sources from SIₓ₁ uniformly until the prescriptive size of the effective source set Iᵣ has been selected, inclusive of x₁.</td>
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</table>

B. Refinement of Noisy Concepts and Web Sources

Since the tags and description sentences of Web images/videos are given by various uploaders with subjectivity and arbitrariness, there are a portion of meaningless words that are irrelevant to the event videos. To make the concepts in the preliminary concept pool have reasonable meaning, we simply filter the tags/keywords by choosing the extensive Nouns and Verbs as well as discarding other words because the Nouns and Verbs can effectively represent the semantics of actions for events [31]. Fig. 2 shows some examples of the concepts that we collected after refining.

After refining the noisy concepts, the Web sources belonging to several concepts are not enough and the quality of the Web sources may be poor. To collect enough valid training examples, for each concept, we first search a large number of images from Google and videos from Youtube by querying the corresponding concept. Then we use the NAPSAC [13] to eliminate the noisy images and videos in each concept training set. Specifically, the images/videos collected at the first stage are treated as the center points, and the radius R is chosen empirically to determine the concept circle. The Web images/videos in the circle are selected as the training examples of the concept. The NAPSAC pseudo-code algorithm is summarized in Algorithm 1.

C. Hierarchical Clustering of Concepts and Their Associated Images/Videos

In the refined pool of preliminary concepts, some different tags/keywords may have similar semantic meaning, so it is essential to merge them into a single meaningful tag/keyword with the semantic consistence of concepts. Accordingly, the associated images/videos of these tags/keywords should also be
combined together to enrich the data set for training an informative concept classifier. Therefore, we introduce the hierarchical clustering [14] to cluster tags/keywords based on both the text similarity of textual descriptions and the visual similarity of their associated images/videos.

Text Similarity: We compute the similarity of two words using the interface of the WordNet [32] in Python API. The API provides a packaged method of calculating the distance of two words. For two short phrases of multiple words (e.g. keywords), we select every word from each phase to compute the relevance of the words, and the maximum similarity score is chosen as the relevance of these two phrases. The text similarity of concept $c_i$ and $c_j$ is defined as $S(T_{text_i}, T_{text_j})$.

Visual Similarity: We use the static and motion features to measure the visual similarity between different concepts. For different concepts $c_i$ and $c_j$, their associated training example sets are $T_{c_i}$ and $T_{c_j}$, respectively. We extract the deep CNN features [33] for the images in the image collection and the motion feature IDT [34] of the videos. A mean representation of all the training examples is used to stand for the whole training set. The text similarity of image/video sets is computed by:

$$S(T_{c_i}, T_{c_j}) = \max(\cosine(MI_{c_i}, MI_{c_j}), \cosine(MV_{c_i}, MV_{c_j})),$$  \hspace{1cm} (1)

where $MI_c$ and $MV_c$ are the image and video mean vectors of the training set of the concept $c$, respectively. We have also investigated other similarity metrics such as Euclidean distance, $\chi^2$ distance and histogram intersection. The cosine similarity strikes the best trade-off between effectiveness and efficiency. So the final similarity between two concepts $c_i$ and $c_j$ is given by:

$$S(c_i, c_j) = \alpha \cdot S(T_{text_i}, T_{text_j}) + (1 - \alpha) \cdot S(T_{c_i}, T_{c_j}),$$  \hspace{1cm} (2)

where $\alpha$ is a tradeoff parameter.

We then adopt the hierarchical clustering to cluster the candidate concepts into $M$ concept groups. The collection of the concepts used in event detection is composed of these $M$ concept groups. The distances between the concepts in each group in the clustering are under a distance threshold $T_{dis}$. We refine the description of each concept group based on the textual of the clustered concepts. Fig. 3 lists several automatically discovered concepts and their image/video training samples we collected in the experiment.

### IV. Model Formulation

#### A. Notation

By using the automatic concept discovery described in Section III, a set of semantic concepts is found, represented by $\mathcal{S} = \{s_1, s_2, \ldots, s_{N_s}\}$, where $N_s$ is the total number of the concepts. For each key segment which is actually a short clip of an video, one related concept from the above set is automatically selected to describe its semantic information. Thus the knowledge learned from Web images and videos belonging to one concept is transferred to the related key segment with the same concept.

Formally, the queried images and videos are collected as the training set $\mathcal{X}^t$ of the source domain $\mathcal{D}^s$. Let $\mathcal{X}^t = \mathcal{X}^t_1 \cup \mathcal{X}^t_2$ represent the set of key segments selected from the $p$-th training subset related to the $p$-th concept in $\mathcal{S}$ with $N_p$, the number of samples of $\mathcal{X}^t_p$, $x_{p,j}^t \in \mathcal{X}^t_p$ denotes the $j$-th sample in the $p$-th training subset, and $y_{p,j}^t \in \mathcal{Y}^t$ denotes the event class label of $x_{p,j}^t$. We model the temporal positions of key segments in a video as $H = [h_1, h_2, \ldots, h_{N_p}]$ and the concepts of these segments as $C = [c_1, c_2, \ldots, c_{N_p}]$, where $c_i$ represents the concept of the $i$-th segment and $N_p$ is the number of the segments. Since the ground truth of $H$ and $C$ are not available in training data, they are treated as latent variables in our method. Then the pre-learned classifier of the $p$-th concept using the training subset $\mathcal{X}^t_p$ is formulated by $f^t(x_p) = w_p^t \cdot \Phi(x_p)$, where $w_p^t$ is the template and $\Phi(x_p)$ is the feature mapping function.

The consumer videos are collected as the training set $\mathcal{X}^d$ of the target domain $\mathcal{D}^t$ with $N_t$, the number of samples of $\mathcal{X}^d$. Let $x_i^d$ indicate the $i$-th sample of $\mathcal{X}^d$ and $y_i^d$ indicate the event class label of $x_i^d$.

#### B. Event Detection Model

The event detection can be formulated as predicting the event class label $y$ of an input video $x$,

$$y = \arg\max_{y,H,C} f(x, y, H, C),$$

where

$$y = \arg\max_{y,H,C} W^t \cdot \Phi(x, y, H, C).$$  \hspace{1cm} (3)

The discriminative function $f(x, y, H, C)$ is composed of a low-level event model, a temporal relation model of the key segments, and an interaction model between the key segments.
and the entire video:

\[
F_{(x,y,H,C)} = W^t \cdot \Phi(x, y, H, C) \\
= F_d(x, H, C) + F_a(H, C) + F_b(H, C, y) \\
= \sum_{k=1}^{N_x} \sum_{g=1}^{N_y} w_k^t \varphi(x, h_g) \cdot I_k(c_g) \\
+ \sum_{k=1}^{N_x} \sum_{p=1}^{N_y} \sum_{q=1}^{N_y} w_a \phi(h_p, h_q) \cdot I_k(c_p) \cdot I_l(c_q) \\
+ \sum_{k=1}^{N_x} \sum_{g=1}^{N_y} w_b \psi(h_g, y) \cdot I_k(c_g),
\]

(4)

where \(W^t = [w_1^t, \cdots, w_{N_x}^t, w_a, w_b]\) is the joint weight vector of \(F\). Each model is defined as follows.

1) Low-Level Event Model (LEM):

\[
F_d(x, H, C) = \sum_{k=1}^{N_x} \sum_{g=1}^{N_y} w_k^t \varphi(x, h_g) \cdot I_k(c_g). 
\]

(5)

The LEM is the most important part in the event detection model, which models the contributions of the low-level features for event detection. \(w_k^t\) is a concatenation of \(w_k^{t_{\text{im}}}\) and \(w_k^{t_{\text{fv}}}\), the image and video target template vectors, respectively. Each video is divided into \(N_y\) shot clips, and each clip can be represented as \(\varphi(x, h_g)\), where \(h_g\) indicates the index of the \(g\)-th clip in video \(x\), and \(c_g\) represents the concept of this clip. \(\varphi(x, h_g) = [\varphi_{\text{im}}(x, h_g), \varphi_{\text{fv}}(x, h_g)]\) is also a concatenation of the image and video feature representation of the \(g\)-th clip. \(I_k(c_g)\) is an indication function, and assigned the value of 1 if \(c_g = k\) and 0 otherwise. The variables \(H\) and \(C\) are not provided during training and testing.

2) Temporal Relation Model (TRM):

\[
F_a(H, C) = \sum_{k=1}^{N_x} \sum_{l=1}^{N_y} \sum_{p=1}^{N_y} \sum_{q=1}^{N_y} w_a \phi(h_p, h_q) \cdot I_k(c_p) \cdot I_l(c_q). 
\]

(6)

Exploiting the temporal relationships between segments is significantly essential for accurately extracting meaningful key segments in event detection. For example, in the event of “basketball”, the segment corresponding to the concept of “passing the ball” often happens before the segment of “shooting the ball”. In the event of “birthday”, the segment of “blow out the candles” often occurs after the segment of “burning candles”.

Therefore, we leverage the temporal relation model \(F_a(H, C)\) in Eq. (6) to capture the temporal relationships between the key segments. \(\phi(h_p, h_q)\) is a temporal vector. When the index \(h_p\) of the key segment happens before \(h_q\), \(\phi(h_p, h_q) = [1, 0]\) and \(\phi(h_p, h_q) = [0, 1]\) otherwise. \(w_a = [w_{a1}, w_{a2}]\) is a template vector, where \(w_{a1}\) indicates the relation score of the \(h_p\)-th segment happening before the \(h_q\)-th segment and \(w_{a2}\) denotes the score of the \(h_q\)-th segment occurring after the \(h_q\)-th segment. \(I_k(c_p)\) is also an indication function with the value of 1 if \(c_p = k\) and 0 otherwise. We initialize \(w_a\) according to the temporal relations of the concepts which correspond to the segments in a video.

3) Segment Event Interaction Model (SEIM):

\[
F_b(H, C, y) = \sum_{k=1}^{N_x} \sum_{g=1}^{N_y} w_b \psi(h_g, y) \cdot I_k(c_g). 
\]

(7)

The interaction between segments and events is also an informative factor in event detection. For example, the probability of the segment of “dog” appears in the high-level event of “dog show” is very high while “dog show” hardly contains the segment of “guitar”.

Fig. 3. Examples of image and video concepts collected automatically from Web. These concepts cover the actions, objects, and scenes.
So we propose the Segment Event Interaction Model to capture the contextual interactions between the key segments and the entire event. When the segment $h_g$ appears in the event $y$, $\psi(h_g, y)$ is assigned to 1. $I_k(c_p)$ is an indication function with the value of 1 if $c_g = k$ and 0 otherwise. $w_h$ is the template vector and we initialize $w_h$ according to the $c_g$-th concept.

V. MODEL LEARNING

A. Objective Function

The source event classifier learned from Web images and videos is formulated as $W = \{w_1^*, w_2^*, \ldots, w_h^*, \ldots, w_N^*, w_n^*, w_a^*, w_b^*\}$, where $w_k^* = [w_{k,m}^*, w_{k,s}^*]$ is the $k$-th SVM classifier trained by images and videos in $X_p^*, w_{k,m}^*$ and $w_{k,s}^*$ are the image and video classifiers. $w_a^*$ and $w_b^*$ are the initial temporal template and interaction template, respectively.

The target classifier $W^t$ is trained by using a limited number of labeled training videos. Given a training video $x_i$ from the target domain, $y_i$ is the ground-truth label of $x_i$, and $y_i^t$ is the optimal label of $x_i$. The parameter vector $W^t$ is learned by the following optimization problem:

$$\min_{W^t} \frac{1}{2} \|\Delta W\|^2 + \lambda_1 \sum_{i=1}^{N_t} \xi_i + \lambda_2 \sum_{i=1}^{N_t} \zeta_i \quad (8)$$

s.t.

$$\max_{H^t, C_t} \mathcal{F}(x_i, y_i, H^t, C_t) - \max_{H^t_i, C^t_i} \mathcal{F}(x_i, y_i^t, H^t_i, C^t_i) \leq L(y_i, y_i^t, H^t_i, C^t_i) - \xi_i, \quad (9)$$

$$0 \leq \xi_i, \forall (x_i, y_i) \in \mathcal{D}^t, \quad (10)$$

$$\sum_{k=1}^{N_t} \sum_{g=1}^{N_s} I_k(C_g) = K, \quad (11)$$

$$\zeta_i = \sum_{m=1}^{N_s} \sum_{n=1}^{N_s} \sum_{p=1}^{N_s} \sum_{q=1}^{N_s} |f_m(x_i, h_p, c_p) - f_n(x_i, h_q, c_q)|, \quad (12)$$

where $\lambda_1, \lambda_2$ are trade-off parameters. $L(y_i, y_i^t, H^t_i, C^t_i)$ is 0–1 loss function defined by $L(y_i, y_i^t, H^t_i, C^t_i) = 0$ if $y_i = y_i^t$ and 1 otherwise. This loss function is used to enforce the decision value of the newly learned target classifier not far away from the source classifier.

The regularization term $\Delta W = W^t - W^s$ is introduced to indicate that the target classifier $W^t$ should be close to the source hyperplane $W^s$. The constraint in Eq. (9) can be explained as follows: for the $i$-th training sample, the score $\max_{H^t, C_t} \mathcal{F}(x_i, y_i, H^t, C_t)$ which is associated with the ground-truth event label $y_i$, latent locations $H^t_i$ and concept $C_t$ should be no less than the score $\max_{H^t_i, C^t_i} \mathcal{F}(x_i, y_i^t, H^t_i, C^t_i)$ which is associated with any hypothesized event label $y_i^t$, segment locations $H^t_i$ and concept $C^t_i$. The constraint in Eq. (11) shows that $K$ key segments are automatically extracted in a video, where $I_k(c_p)$ is an indication function and is assigned to 1 when $c_g = k$, showing that the concept $k$ has been localized in the $g$-th clip.

We also append another constraint in Eq. (12) for extracting more informative key segments. This indicates that all the selected concepts are important to detect events and the decision values of the detected key segments should be close to each other. $f_m(x_i, h_p, c_p)$ denotes the decision value of the $h_p$-th key segment in video $x_i$, defined by

$$f_m(x_i, h_p, c_p) = w_m^t \varphi(x_i, h_p) \cdot I_m(c_p), \quad (13)$$

B. Optimization

In order to solve the non-convex optimization problem in Eq. (8), we first select $K$ fixed concepts, then an iteration optimization algorithm is proposed to alternate between inferring the unobservable $(H^t_i, C_t)$ given the pair $(x_i, y_i)$ and solving the standard structural SVM when $(H^t_i, C_t)$ is observable. After learning the fixed target classifier, we re-select $K$ optimal key segments corresponding to the concepts with a dynamic programming algorithm.

1) Finding the Optimal Target Classifier With Fixed K Concepts: We fix the selected $K$ concepts corresponding to the key segments in the video. With the fixed $K$ concepts, Eq. (8) turns to be the latent structural SVM model:

$$\min_{W^t} \frac{1}{2} \|\Delta W\|^2 + \lambda \sum_{i=1}^{N_t} \mathcal{R}_i(W^t), \quad (14)$$

and $\mathcal{R}_i(W^t)$ is a hinge loss function defined as

$$\mathcal{R}_i(W^t) = \max_{H^t_i, C_t} \mathcal{F}(x_i, y_i, H^t_i, C_t) - \max_{H^t_i, C^t_i} \mathcal{F}(x_i, y_i^t, H^t_i, C^t_i) + L(y_i, y_i^t, H^t_i, C^t_i)$$

$$+ \sum_{m=1}^{N_s} \sum_{n=1}^{N_s} \sum_{p=1}^{N_s} \sum_{q=1}^{N_s} |f_m(x_i, h_p, c_p) - f_n(x_i, h_q, c_q)|, \quad (15)$$

where

$$(H^t_i, C^t_i) = \arg\max_{H^t_i, C_t} \mathcal{F}(x_i, y_i, H^t_i, C_t), \quad (16)$$

$$y_i^t = \arg\max_{y_i} \mathcal{F}(x_i, y_i, H^t_i, C^t_i). \quad (17)$$

We adopt a non-convex cutting plane method proposed in [35] to solve the non-convex optimization problem. The non-convex cutting plane method aims to iteratively build an increasingly accurate piece-wise quadratic approximation of $\mathcal{R}_i(W^t)$ based on its sub-gradient $\partial W^t \cdot \mathcal{R}_i(W^t)$. Now the primary task is to compute the sub-gradient $\partial W^t \cdot \mathcal{R}_i(W^t)$. The sub-gradient $\partial W^t \cdot \mathcal{R}_i(W^t)$ can be computed by

$$\partial W^t \cdot \mathcal{R}_i(W^t) = \sum_{k=1}^{N_s} \sum_{g=1}^{N_s} \varphi(x, h_g) \cdot I_k(c_g) \quad - \sum_{k=1}^{N_s} \sum_{g=1}^{N_s} \varphi(x, h_g) \cdot I_k(c_g^t). \quad (18)$$
\[ \begin{align*}
&+ \sum_{k=1}^{N_c} \sum_{l=1}^{N_c} \sum_{p=1}^{N_s} \sum_{q=1}^{N_s} \phi(h_p, h_q) \cdot I_k(c_p) \cdot I_l(c_q) \\
&- \sum_{k=1}^{N_c} \sum_{l=1}^{N_c} \sum_{p=1}^{N_s} \sum_{q=1}^{N_s} \phi(h_p^*, h_q^*) \cdot I_k(c_p^*) \cdot I_l(c_q^*) \\
&+ \sum_{k=1}^{N_c} \sum_{l=1}^{N_c} \psi(h_q, y) \cdot I_k(c_q) \\
&- \sum_{k=1}^{N_c} \sum_{l=1}^{N_c} \psi(h_q^*, y) \cdot I_k(c_q^*) \\
&+ \sum_{m=1}^{N_s} \sum_{n=1}^{N_s} \sum_{p=1}^{N_s} \sum_{q=1}^{N_s} \varphi(x_i, h_p) \cdot I_m(c_p) \\
&- \varphi(x_i, h_q) \cdot I_n(c_q) \cdot A, \quad (18)
\end{align*} \]

where \( A = \left\| f_m(x_i, h_p, c_p) - f_n(x_i, h_q, c_q) \right\| \).

2) Finding the Optimal \( K \) Concepts With Fixed \( W^t \): When fixing \( W^t \), Eq. (8) turns into a 0–1 integer programming problem:

\[ \max \sum_{i=1}^{N_t} \sum_{k=1}^{N_c} \sum_{l=1}^{N_c} f_k(x_i, h_q, c_q) \quad (19) \]

s.t.

\[ \sum_{k=1}^{N_c} \sum_{l=1}^{N_c} I_k(c_q) = K, \quad (20) \]

\[ I_k(c_q) = 0/1, \forall k \in [1, N_c], \forall q \in [1, N_s]. \quad (21) \]

We use the dynamic programming algorithm to resolve this problem. The main issue is how to select the top \( K \) concepts relevant to the key segments in videos from the concept collection \( S \) with \( N_c \) concepts. There are two conditions to select \( K \) concepts from \( S \): (i) Select \( K \) concepts from \( N_c \) concepts. (ii) Select \( K \) concepts from \( N_c \) concepts and select the \( N_c \)-th concept. We choose the max value of these two conditions. Let \( EV(N_c) \) represent the decision value of the \( N_c \)-th concept in event detection formulated as

\[ EV(N_c) = \sum_{i=1}^{N_t} \sum_{g=1}^{N_s} w_{N_c} \varphi(x_i, h_g) I_{N_c}(c_g). \quad (22) \]

The procedure of dynamic programming can be defined as

\[ E(N_s, K) = \max (E(N_s - 1, K), E(N_s - 1, K - 1) + EV(N_s)), \quad (23) \]

The detailed optimization algorithm for complex event detection is summarized in Algorithm 2.

VI. EXPERIMENT

We evaluate the proposed method on two datasets: the TRECVID2014 Multimedia Event Detection dataset [36] and the Columbia’s Consumer Video (CCV) dataset [37]. The mean of Average Precision (mAP) for binary classification [8] is applied for performance evaluation.

A. Datasets

The CCV dataset contains 9,317 Youtube videos over 20 event categories with a training set of 4,659 videos and a test set of 4,658 videos. Since our work focuses on event detection, the object/scene categories such as “bird”, “beach”, “cat”, “dog” and “playground” are discarded. Finally, 15 event categories are utilized in our experiments.

The TRECVID MED2014 dataset contains 40 categories of events. The partition of “Background” contains 4,983 Background videos which do not belong to any events and can be used as negative examples in the training procedure. The partitions of “10EX” and “100EX” respectively consist of 10 and 100 positive videos for each of the pre-defined 20 event classes. In our experiment, the setting of “10EX” and “100EX” are adopted. The partition of “MEDIast” contains 29,200 videos, in which there are about 25 positive samples for each event class and 26,171 negative videos. Fig. 4 shows several examples of the frames from the test videos on the CCV and the MED2014 datasets, respectively.

The Self-Collect ed Image and Video Dataset is constructed by the videos collected from the Youtube Website and the images collected from the Google and Flickr Websites. First, we query about 4,000 images (200 images per class) from the Flickr Website and 600 videos (30 videos per class) from the Youtube
website by using the name of event class as search keywords. Then, the associated tags and description sentences of the queried images and videos are collected to construct the preliminary concept pool. To guarantee the adequacy of the training data for each concept, we re-search about 40,000 images and 1000 videos based on the concept pool from the Google website and the Youtube website, respectively. Finally, for each concept, there are 200 images and 50 videos collected from the Web source.

B. Experiment Setup

1) Visual Features: The visual description of an image/frame is represented by a 4096-dimensional CNN feature vector which is the output of the 16-layer VGG model [38] implemented by Caffe toolkit [33]. Each image/frame is scaled to $256 \times 256$, and cropped to a random $227 \times 227$ region. The length of each clip is 10 seconds and there is 5 seconds overlap between two adjacent video clips. For a video segment, we first extract the improved dense trajectory (IDT) [34], and compute three descriptors (i.e. Histogram of Gradients (HOG), Histogram of Optical Flow (HOF), and Motion Boundary Histogram (MBH)) of IDT. Then a local descriptor encoding method called Vector of Locally Aggregated Descriptors [6], [39] is used to encode the three descriptors as the visual feature of the video segment.

2) Concept Classifiers: In this experiment, 120 concepts are automatically discovered by using the methods in the Section III. After collecting the images and videos from Web, there are about 500 images and 20 videos in the training dataset for each concept. These images and videos are treated as positive samples, while the negative samples are constructed by randomly selecting images and videos from the training datasets of other concepts. The proportion of the positive and negative samples is set to 1:5. We use the LIBSVM toolkit [40] with the linear kernel to learn the concept image and video classifiers. The 5-fold cross-validation is utilized to choose the parameter of regularization coefficient $C$ in the SVM.

3) Related Methods: We compare our method with several related methods on both the CCV dataset and the MED2014 dataset, such as the target domain SVM ($SVM_T$), Domain Adaptive SVM (DASVM) [41], Domain Adaptation Machine (DAM) [42], and Domain Selection Machine (DSM) [18]. $SVM_T$ is trained on the limited number of the training videos we utilize in our method. DASVM is a single domain method in which the images and videos are gathered together as a single domain. Both DAM and DSM are multi-source domain adaptation methods where the training samples belonging to each concept are treated as a single domain.

In the respect of event detection with key segments, our method is compared with Dynamic Pooling with Segment Pairs (DPSP) [23], Evidence Localization Model (ELM) [5], and Joint Event Detection and Recounting (JEDaR) [24] on the MED 2014 dataset. Additionally, we compare the proposed method with TagBook [43], VideoStory [44], and Fusion for Visual Recognition (RFVR) [45] on the CCV dataset. DPSP and ELM both dynamically locate the key segments of videos for event detection. JEDaR simultaneously detects high-level events and localizes the indicative concepts of the events. We compare these three methods on the MED 2014 dataset. TagBook and VideoStory propose to learn the semantic video representation for event detection. RFVR models the dependency based on probabilistic properties of posteriors without any assumption on the data distribution for visual recognition. These three methods are tested on the CCV dataset.

C. Results

1) Comparison With Related Methods: Tables I–III list the per-class average precision of different methods on the TRECVID MED 2014 EK100, EK10 and CCV datasets, respectively. It is obvious that our approach performs better than other related methods. With analysis into more details, we have the following observations:

1) When compared with the SVM_T, our method achieves superior results which verifies the advantage of exploiting
the key segments for event detection as well as automatically discovering concepts for event description in our framework.

2) When compared with DASVM, DAM, DSM, Videostory, Tagbook and RFVR, our method performs better. It is possible that our method mainly focuses on detecting the key segments to classify the complex videos with the benefit of efficiently investigating the underlying structural information of videos for the recognition task.

3) Our method outperforms the segment-based methods of DPSP, ELM and JEDaR on the MED 2014 dataset, which validates that it is beneficial to transfer the knowledge learned from Web resources to the target videos for improving the accuracy of event detection model.

4) Our method also achieves better results on the TRECVID EK10 dataset, which validates the effectiveness of our method on few-shot learning.

5) For most of the events such as “marriage proposal”, “beekeeping”, “baseball” and “birthday”, our method obtains significant results owing to the discovered discriminative and descriptive key segments in detecting videos. For some events of “giving direction to a location”, “fixing musical instrument” or “tuning musical instrument”, our method performs a little worse, the possible reason is that

### Table I

<table>
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<td>12.72</td>
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<td>23.56</td>
<td>25.21</td>
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TABLE III
AVERAGE PRECISION (%) OF PER-CLASS PERFORMANCE ON CCV OF DIFFERENT METHODS

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<td>Basketball</td>
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<td>42.33</td>
<td>36.59</td>
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<td>77.83</td>
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<td>36.1</td>
<td><strong>38.5</strong></td>
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<td>45.4</td>
<td>55.59</td>
<td><strong>58.46</strong></td>
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<td>52.1</td>
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TABLE IV
THE RESULTS OF DIFFERENT COMPONENTS ON COMPLEX EVENT DETECTION MODEL

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<th>Dataset</th>
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<th>TRM</th>
<th>SEIM</th>
<th>w/o LEM</th>
<th>w/o TRM</th>
<th>w/o SEIM</th>
<th>(\lambda_1 = 0)</th>
<th>(\lambda_2 = 0)</th>
<th>Ours</th>
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<tr>
<td>CCV</td>
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<td>11.84</td>
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<td>62.38</td>
<td>15.64</td>
<td>60.53</td>
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<td>MED2014 (EK10)</td>
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<td>3.98</td>
<td>2.63</td>
<td>6.84</td>
<td>22.63</td>
<td>25.59</td>
<td>3.63</td>
<td>22.48</td>
<td><strong>26.57</strong></td>
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<tr>
<td>MED2014 (EK100)</td>
<td>23.68</td>
<td>4.85</td>
<td>2.92</td>
<td>7.92</td>
<td>25.58</td>
<td>28.85</td>
<td>5.21</td>
<td>28.68</td>
<td><strong>31.29</strong></td>
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TABLE V
THE RESULTS OF DIFFERENT COMPONENTS IN THE PROCEDURE OF AUTOMATIC CONCEPT DISCOVERY

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<tr>
<th>Dataset</th>
<th>w/o NAPSAC</th>
<th>w/o Cluster</th>
<th>w/o Text</th>
<th>w/o Visual</th>
<th>Ours</th>
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<td>MED2014(EK10)</td>
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<td>22.83</td>
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<td>MED2014(EK100)</td>
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<td>20.38</td>
<td>28.47</td>
<td>12.41</td>
<td><strong>31.29</strong></td>
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</table>

Fig. 5. The changes of mean average precision (%) with the radiuses in the procedure of eliminating noisy images.

Fig. 6. The changes of mean average precision (%) with the radiuses in the procedure of hierarchical clustering.

it is difficult to describe these events with informative concepts.

2) Analysis of Different Components on Event Detection Model: We investigate the effects of each component and each constraint in Eq. (8). As given in Table IV, “w/o LEM”, “w/o TRM” and “w/o SEIM”, indicate the methods of removing the low-level event model, removing the temporal model, and removing the concept event joint model, respectively. “\(\lambda_1 = 0\)” and “\(\lambda_2 = 0\)” indicate the methods of removing the constraints, respectively. It is interesting to notice that: (i) When discard-
Fig. 7. The key segments (bright color) in videos (blue color) of several events we extracted in our experiment.

ing the LEM model, the detection performances significantly degrade on both the MED 2014 and the CCV datasets, which clearly demonstrates the importance of utilizing the low-level feature representation to train the discriminative concept classifiers for key segments detection. (ii) The performance is obviously improved when integrating either the TRM model or the SEIM model, because either the temporal relationship between different concepts or the context relationship between concepts and specified events is helpful for selecting more discriminative and descriptive concepts for event videos with filtering out the unreasonable and inaccurate concepts. (iii) The mAP decreases when either of the constraints is removed from Eq. (8), which confirms that the contributions of the selected concepts in the specified event are close and the correlations between the target training samples provide effective information to train the target classifier.

3) Analysis of Different Components on Automatic Concept Discovery: Table V lists the results of different components on automatic concept discovery, where “w/o NAPSAC” and “w/o Cluster” respectively represent the methods of excluding the NAPSAC procedure and the hierarchical clustering method in the concept discovery model. “w/o Text” and “w/o Visual” indicate the methods of excluding the text similarity and the visual similarity in hierarchical clustering separately. From the results, we can observe that (i) NAPSAC is very important to find the discriminative concepts by filtering out those noisy videos and images. (ii) The hierarchical clustering of the text description of the concepts as well as the images and videos belonging to each concept is capable of improving the detection accuracy as the hierarchical clustering method could cluster the similar concepts which are similar in text description or visual representation into one new concept. Additionally, during the clustering, it is essential to employ both the textual and visual information of images and videos to measure the similarity between two samples.

4) Evaluations on Different Radiuses in Automatic Concept Discovery: Fig. 5 shows the mean average precision (mAP) of different radiuses for eliminating noisy Web images/videos in automatic concept discovery. The parameter of radius determines the number of relative images/videos in each concept. As shown in Fig. 5, the radius is set to 1 and 1.1 on the CCV and the MED2014 datasets, respectively, to achieve the best
performance. When the radius becomes lower or higher from

the best value, the mAP will obviously decrease. The possible

explanation is that when the radius is smaller, there will be not

enough relative training examples to be clustered of each new

concept, this will cause over-fitting of the concept classifiers.

When the radius is larger, there will be more noisy images and

videos in the concept, and the training data from each concept

may lose the discriminability.

In Fig. 6, we illustrate the performances of different values

of radius for hierarchical clustering of concepts in automatic

cracy of the textual description and the visual similarity of the

terface with each other. Once either similarity

has reached the radius, the two corresponding concepts will

be clustered to generate one new concept. In the CCV and the

and MED2014 datasets, the best value of radius is 0.55 with the

highest detection accuracy. When the radius becomes smaller,

the similar concepts may be ignored to be together. On the con-

trary, when the radius becomes larger, more irrelevant concepts

will aggregate into one cluster. In both of these two cases, the

accuracy of concept classifiers will degrade resulting in the worse

performance of the event detection model.

5) Key Segments of Videos for Event Detection: The seg-

mentation results of several events have been shown in Fig. 7. In

Fig. 7, four segments of “knee down”, “stand opposite”, “hug”,

and “kiss” are detected in the event of “marriage proposal”. For

other events, we could also detect each four segments in the

same way. The segmentation of videos makes event detection

more meaningful and practical.

VII. CONCLUSION

In this paper, we have proposed a framework of automatically
detecting key segments for event detection by leveraging loosely
labeled Web sources and a limited number of consumer videos.

A discriminative model is presented for complex event detec-
tion by using an adaptive latent structural SVM model, where

the locations of key segments are regarded as latent variables.

The NAPSAC and hierarchical clustering are combined to au-
tomatically construct more meaningful concepts which are treated

as the semantic descriptions of the key segments and the tem-

poral information of concepts is exploited to capture the temporal

relations between segments. The experimental results on the

Columbia’s Consumer Video dataset and the TRECVID2014
Multimedia Event Detection dataset demonstrate the effective-

ness of our method.

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Hao Song received the B.S. degree from North China Electric Power University, Baoding, China, in 2012. He is currently working toward the Ph.D. degree under the supervision of Prof. Y. Jia with Beijing Laboratory of Intelligent Information Technology, School of Computer Science, Beijing Institute of Technology, Beijing, China. His research interests include computer vision, machine learning, and video retrieval.

Xinxiao Wu received the B.A. degree in computer science from Nanjing University of Information Science and Technology, Nanjing, China, in 2005, and the Ph.D. degree in computer science from Beijing Institute of Technology, Beijing, China, in 2010. She is currently an Associate Professor with the School of Computer Science, Beijing Institute of Technology. Her research interests include machine learning, computer vision, and human action perception.

Wennan Yu received the B.S. degree in 2015 from Beijing Institute of Technology, Beijing, China, where he is currently working toward the M.S. degree under the supervision of Prof. X. Wu with Beijing Laboratory of Intelligent Information Technology, School of Computer Science. His research interests include computer vision and machine learning.

Yunde Jia received the B.S., M.S., and Ph.D. degrees in mechatronics from Beijing Institute of Technology (BIT), Beijing, China, in 1983, 1986, and 2000, respectively. He is a Professor of computer science with BIT, where he is the Director of Beijing Laboratory of Intelligent Information Technology. He has previously served as the Executive Dean of the School of Computer Science, BIT, from 2005 to 2008. He was a Visiting Scientist with Carnegie Mellon University from 1995 to 1997 and a Visiting Fellow with the Australian National University in 2011. His current research interests include computer vision, media computing, and intelligent systems.

Hao Song received the B.S. degree from North China Electric Power University, Baoding, China, in 2012. He is currently working toward the Ph.D. degree under the supervision of Prof. Y. Jia with Beijing Laboratory of Intelligent Information Technology, School of Computer Science, Beijing Institute of Technology, Beijing, China. His research interests include computer vision, machine learning, and video retrieval.