A Novel Topic Extraction Method based on Bursts in Videos Streams

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Abstract

In this paper, we introduce a novel method for extracting "topics" as interesting events in a video. Here, we define the interestingness of an event by the anomaly of a target character's appearance and disappearance pattern. As examples of abnormal patterns, shot durations in thrilling events are very short while shot durations in romantic events are very long. In contrast, as an example of non-abnormal pattern, conversation events are presented by the pattern, where the target character repeatedly appears in one shot and then another character appears in the next shot. From the above point of view, our topic extraction method aims to detect the following two types of abnormal patterns, called "bursts". The first type of burst is a pattern where the target character appears in shots with very short durations, while the second is a pattern where he/she appears in shots with very long durations. To detect such bursts, we firstly divide the video into events characterized by specific patterns of the target character's appearance and disappearance. We locate these patterns in the video by using time series segmentation technique. Then, we extract topics by examining whether the pattern in each event can be regarded as a burst or not. Experiments on different videos validate that a character's appearance and disappearance patterns are effective for obtaining semantically meaningful events. And, bursts are useful for extracting many interesting topics.

1. Introduction

Due to the recent advance of multimedia technologies, we can access a large amount of videos distributed on the internet or stored in hard disks. As such, users would benefit from the efficient retrieval of events of interest. Thus, many research efforts have been conducted on event retrieval in videos. For event retrieval, one of the most important tasks is ``video segmentation" which divides a video into events. After that, events which match with user's query are returned. Hence, the accuracy of video segmentation is crucial to retrieve events which are semantically meaningful to the user.

Most of existing video segmentation methods define events based on "similarities of low-level features", such as color, motion and audio (e.g. [4], [5], [6], [7], [8], [9]). For example, in an event which happens in a mountain, most shots commonly contain greenish vegetation in the background. Also, in an action event where characters actively move, most shots contain large amounts of motion. And, such an event frequently involves music in order to emphasize the mood. Based on the above observation, the researchers define an event as a set of shots that not only have similar low-level features but also are temporally close to each other. But, in many cases, semantically meaningful events cannot be defined by low-level features, since one event can have significantly different low-level features depending on camera and editing techniques.

In this paper, we define an event based on high-level features, that is, a target character's appearance and disappearance. The idea behind this is that a semantically meaningful event is characterized by an interaction between the target character and other characters. For example, in an event where only the target character performs an action (e.g. taking a walk), he/she appears in most shots. On the other hand, in an event where the target character interacts with other characters (e.g. talking with other characters), shots where he/she appears and shots where other characters appear are repeated one after the other. Inspired by the above idea, we define an event by the pattern of the target character's appearance and disappearance.

But, note that patterns are not so clear for actual events. Let us consider a conversation event where the target character talks to another character. Here, depending on their spoken lines, shot durations are varied. Also, the repetition of shots where the target character appears and shots where another character appears is broken, if a new character participates in the conversation. Furthermore, the target character and another character may stop the conversation for a while. Like this, even in an event, the pattern of the target character's appearance and disappearance is disturbed by various factors. Thus, we incorporate a probabilistic function into our video segmentation, so that the video is divided into events characterized by probabilistically distinct patterns.

Afterward, in order extract interesting events as "topics", we consider the following video editing technique; a professional video editor tailors a rhythm of shot durations, so that the central action in these shots is not disturbed [3]. Typically, shot durations are very short in thrilling events while they are very long in romantic events. Based on this video editing technique, we extract topics as events containing one of the following two types of abnormal patterns, called "bursts". As shown in Figure 1 (a), in the first type of burst, the target character appears in shots with very short durations, while in the second, he/she appears in shots with very long durations.

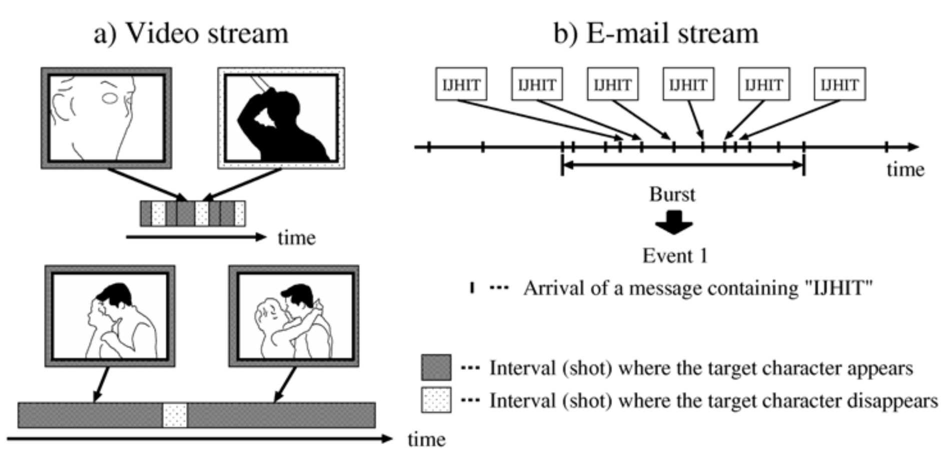

Figure 1. Comparison between bursts in a video stream and bursts in an e-mail stream.

Bursts are intensively studied in the field of data mining, where researchers detect bursts to extract useful knowledge from various data, such as financial data [11] and traffic data [12]. Among the bursts studied, a particularly famous type of burst exists in text streams such as the e-mail stream in Figure 1 (b) [2], [10]. Here, a burst is defined as an abnormally large number of massage arrivals containing a certain keyword. It characterizes an event related to the keyword. For example, in Figure 1 (b), an author writes a paper and submits it to the "International Journal of Hybrid Information Technology (*IJHIT*)" in *Event 1*. This event is characterized by many arrivals of messages containing the keyword *IJHIT* because the author actively discusses the paper with co-authors via e-mail.

Note that bursts in an e-mail stream are defined on messages associated with time stamps. That is, as shown in Figure 1 (b), message arrivals are represented as vertical lines on the time axis. On the other hand, a video is a "continuous media" which conveys the semantic contents only when media quanta (i.e. video frames) are continuously played in time [13]. So, as can be seen from dark-shaded intervals in Figure 1 (a), the target character continuously appears in time intervals (i.e. shots). Therefore, we define bursts in the video based on intervals of the target character's appearance. To our best knowledge, this kind of interval-based burst has not been proposed yet.

2. Basic Concept

In this section, we describe basic concepts which are necessary for our topic extraction method. First, we use Figure 2 to explain our video representation from the viewpoint of a target character. In Figure 2, the female character *A* appears in *shot 1* and *shot 3* and does not appear in *shot 2*. So, if she is a target character, we can create the sequence in the bottom part of Figure 2. In this sequence, dark-shaded intervals represent shots where *A* appears on the screen, while light-shaded ones represent shots where she disappears from the screen. Similarly, if a character *B* or *C* is a target character, we can construct a sequence of intervals of his appearance and disappearance. In this way, by targeting a certain character, the video can be represented as a one-dimensional time series, that is, "a sequence of intervals of his/her appearance and disappearance".

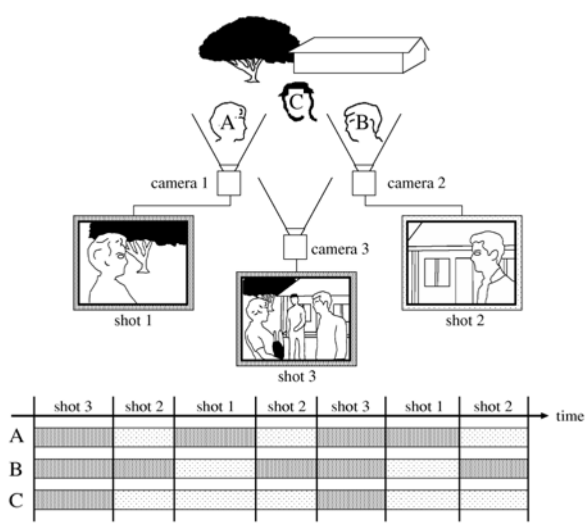

Figure 2. Character's appearance and disappearance

In the above sequence, both of a character's appearance and disappearance are valuable to characterize semantic contents in the video. Clearly, the character's appearance is essential to show his/her action on the screen. In addition, the character's disappearance indicates whether he/she is important in the story. This corresponds to the following video editing technique: in order not to interrupt viewer's interest, a video editor rarely uses redundant shots [3]. This means that “important” characters appear in many shots while “unimportant” characters appear in few shots. For example, in the conversation event in Figure 2, *A* and *B* mainly talk and *C* eavesdrops on their conversation. This event mainly consists of *shot 1* and *shot 2*, so that the editor concentrates viewer's interest on the conversation of *A* and *B*. But, if only *shot 1* and *shot 2* are used, the viewer forgets *C*. So, in order to remind the viewer of *C*, the editor sometimes uses *shot 3*. As a result, an unimportant character *C* appears only in a few shots and disappears in the rest of shots, as shown in the intervals of *C*'s disappearance in Figure 2. Like this, invisible information, that is, a character's disappearance is also useful for analyzing semantic contents in the video.

From now, we explain our video segmentation using the sequence of intervals of *A*'s appearance and disappearance in Figure 3. In order to clarify our notions, we transform the sequence into the bar graph representation, as shown in the bottom of Figure 3. To construct this, we rotate each interval by 90 degrees to transform it into a vertical bar. So, the duration of the interval is equivalent to the height of the bar. Then, bars representing intervals of *A*'s appearance are directed upward and those of disappearance are directed downward. Finally, bars are located on the horizontal axis in the temporal order.

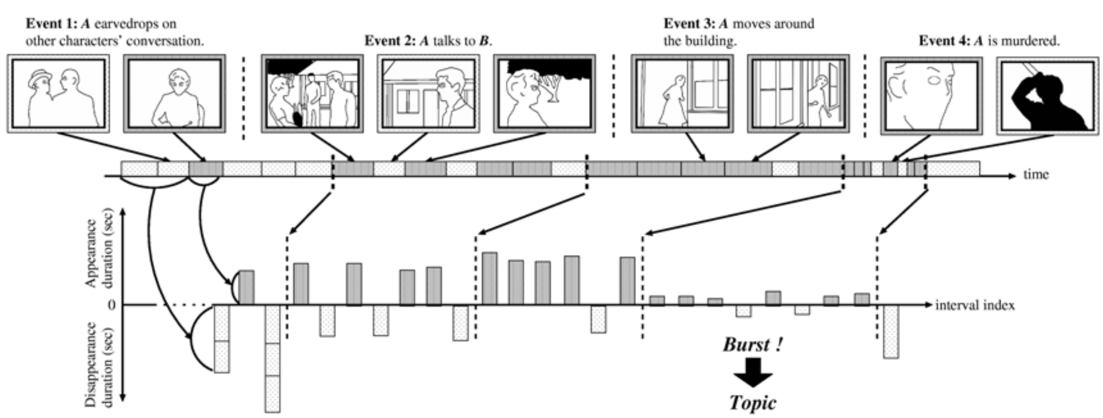

Figure 3. A concept of our video segmentation based on a character’s appearance and disappearance

The bar graph representation in Figure 3 clearly visualizes that each event is characterized by the specific pattern of *A*'s appearance and disappearance. First of all, in *Event 4* where *A* is murdered, the durations of all shots are very short, so the durations of *A*'s appearance and disappearance are very short. Compared to *Event 4*, the other events *Event 1*, *Event 2* and *Event 3* are less thrilling, and are characterized by the much longer durations of *A*'s appearance and disappearance. Especially, in *Event 1* where *A* is an unimportant character, the durations of her disappearance are very long.

Like this, a semantically meaningful event is characterized by the pattern of a target character's appearance and disappearance.

However, it is insufficient to characterize events only by the above patterns. Let us consider the following example. In Figure 3, the durations of *A*'s appearance and disappearance in *Event 2* and *Event 3* are almost the same. But, it is clear that *Event 2* and *Event 3* are semantically different. In order to discriminate such events, we consider an “occurrence ratio” between a target character's appearance and disappearance. Thereby, we can see that *Event 2* and *Event 3* are characterized by significantly different occurrence ratios for *A*'s appearance and disappearance. Specifically, in *Event 2*, *A*'s appearance is frequently followed by *B*'s appearance. So, the number of *A*'s appearance (4 occurrences) is nearly equal to that of her disappearance (3 occurrences). On the other hand, in *Event 3*, she appears in most shots. So, the number of *A*'s appearance (5 occurrences) is much larger than that of her disappearance (1 occurrence). Therefore, we characterize a semantically meaningful event by both the pattern of the target character's appearance and disappearance, and the occurrence ratio.

3. Topic Extraction by Burst Detection

In this section, we describe our topic extraction method. First, we explain our video segmentation method. Then, we present an evaluation measure to examine whether each event contains a burst or not.

3.1. Video Segmentation Method

To begin with, a sequence of intervals of a target character's appearance and disappearance is formulated as follows:

$$X = x_1, x_2, x_3, \Lambda\ , x_N \qquad\qquad x_i = (a_i, d_i) \tag{1}$$

In this equation, $a_i \in \{A(ppearance), D(isappearance)\}$ represents the type of i-th interval and $d_i \in \mathfrak{R}$ represents its duration. Then, we use time series segmentation technique to divide X into the sequence E consisting of non-overlapping K events ($K \ll N$) [1]:

$$E = e_1, e_2, e_3, \Lambda\ , e_K \qquad\qquad e_i = x_a, x_{a+1}, \Lambda\ , x_b \tag{2}$$

That is, e_i is the subsequence from a-th interval to b-th interval in X.

For each event e_i, we evaluate whether it is characterized by the pattern of the character’s appearance and disappearance and the occurrence ratio. For this purpose, we use the following probabilistic function $p(e_i)$:

$$p(e_i) = \prod_{j=a}^{b} p(x_j) = \prod_{j=a}^{b} \begin{cases} p_A(d_j)p(A) & if \quad a_j = A \\ p_D(d_j)p(D) & if \quad a_j = D \end{cases} \tag{3}$$

Here, for each interval $x_j = (a_j, d_j)$ in e_i, we use the following probabilistic distributions to compute the probability of x_j, that is, $p(x_j)$:

- $p(a_j)$ consists of the probabilities of an appearance interval $p(A)$ and a disappearance interval $p(D)$. That is, $p(a_j)$ represents the probability distribution of the type a_j. If types of all intervals in e_i follow a single probability distribution $p(a_j)$ with a high probability, we can regard that the occurrence ratio is invariant in e_i.

- $p_A(d_j)$ and $p_D(d_j)$ represent the probability distributions of the duration of the character's appearance d_j and the duration of his/her disappearance d_j, respectively. That is, we use $p_A(d_j)$ and $p_D(d_j)$ to evaluate the similarity of durations of the character's appearance and the similarity of durations of his/her disappearance, respectively. In the rest of this paper, for the simplicity, we abbreviate "durations of a character's appearance" and "durations of his/her disappearance" as "appearance durations" and "disappearance durations", respectively.

Thus, given $p(a_j)$, $p_A(d_j)$ and $p_D(d_j)$, $p(e_i)$ represents the joint probability of all intervals in e_i. Consequently, $p(e_i)$ provides an overall evaluation value for determining e_i as the subsequence from a-th to b-th interval in X.

Note that the above discussion assumes $p(a_j)$, $p_A(d_j)$ and $p_D(d_j)$ are already known. But, they are generally unknown. In other words, for e_i, we have to determine the pattern of the character's appearance and disappearance and the occurrence ratio. To this end, we estimate the optimal $p(a_j)$, $p_A(d_j)$ and $p_D(d_j)$ which maximize $p(e_i)$. For $p(a_j)$, we can estimate the optimal $p(a_j = A)$ and $p(a_j = D)$ as $N_A^{e_i} / N^{e_i}$ and $N_D^{e_i} / N^{e_i}$, respectively.[1] Here, N^{e_i} is the total number of the character's appearance and disappearance in e_i. Also, $N_A^{e_i}$ and $N_D^{e_i}$ are the number of the character's appearance and that of his/her disappearance, respectively.

For $p_A(d_j)$ and $p_D(d_j)$, we have to represent probabilities of appearance and disappearance durations. With respect to this point, an exponential distribution is generally used to model waiting times for events which occur at a constant rate in time [15]. It is well-known that waiting times for system failures and phone calls are appropriately modeled by exponential distributions. We consider that such exponential distributions can be applied to appearance and disappearance durations for the following reasons. An appearance duration corresponds to a waiting time for a character's disappearance, while a disappearance duration corresponds to a waiting time for his/her appearance. In addition, if the character is a main character, the rate of switching between his/her appearance and disappearance is assumed to be constant and high throughout the video. It is because the character appears many times where his/her various actions are presented, while he/she disappears many times where various reactions from other characters are presented. Thus, for $p_A(d_j)$ and $p_D(d_j)$, we use the following exponential distributions:

$$\begin{aligned} p_A(d_j) &= \lambda_A^{e_i} \cdot e^{-\lambda_A^{e_i} d_j} \\ p_D(d_j) &= \lambda_D^{e_i} \cdot e^{-\lambda_D^{e_i} d_j} \end{aligned} \tag{4}$$

Here, the optimal $p_A(d_j)$ has the parameter $1/\lambda_A^{e_i}$ which is the mean appearance duration in e_i, while the optimal $p_D(d_j)$ has the parameter $1/\lambda_D^{e_i}$ which is the mean disappearance duration.[1] In this way, given e_i, we firstly estimate the optimal $p(a_j)$, $p_A(d_j)$ and $p_D(d_j)$. Then, by applying them to equation (3), we compute $p(e_i)$.

Based on $p(e_i)$, we aim to divide X into K events with the highest probability. To do so, we maximize the following joint probability of K events in X:

$$P(X) = \prod_{i=1}^{K} p(e_i) \tag{5}$$

[1] This can be proven by taking the logarithm of $p(e_i)$, substituting $p(a_j = D)$ with $1 - p(a_j=A)$ and differentiating $\log p(e_i)$.

In order to simplify $P(X)$, we maximize $P'(X) = \log P(X) = \sum_{i=1}^{K} \log p(e_i)$. Note that log() is a monotonically increasing function, so the result of maximizing $P(X)$ is equivalent to that of maximizing $\log P(X)$. The above kind of summation maximization problem can be optimally solved by a dynamic programming technique [1]. Since it requires a very high computational cost $O(N^2K)$, some techniques have been proposed to compute an approximately optimal maximization with a much lower cost [1]. But, we use the dynamic programming technique to obtain the optimal K events. Thereby, we can accurately examine the anomaly of appearance durations in each event, that is, a burst.

3.2. Burst Intensity Measure

In order to evaluate whether each event e_i contains a burst or not, we use the following evaluation measure of "burst intensity (BI)". Here, the burst intensity of e_i represents the degree of anomaly in appearance durations.

$$BI(e_i) = \frac{T_A^{e_i}}{T^{e_i}} \times \int_0^{\infty} | \lambda_A^{e_i} \cdot e^{-\lambda_A^{e_i} x} - \overline{\lambda_A} \cdot e^{-\overline{\lambda_A} x} | \, dx \tag{6}$$

In this equation, T^{e_i} is the total duration of e_i and $T_A^{e_i}$ is the total duration of a character's appearance in e_i. So, the first term is a weight. This means that if the character appears for a longer duration, he/she plays a more important role. The second term represents the difference between the exponential distribution estimated from appearance durations in e_i and the exponential distribution estimated from appearance durations in the whole video. So, a large difference indicates that e_i contains either abnormally short or long appearance durations. Therefore, if $BI(e_i)$ is larger than the pre-defined threshold, e_i is regarded as a topic where a burst occurs.

4. Experiments

In order to test our topic extraction method, we use four movies, *PSYCHO* (the target character is *Marion*), *Star Wars Episode II* (*Anakin*), *River Runs Through It* (*Paul*) and *Mr. Bean* (*Bean*). Since our current method for recognizing a target character cannot achieve a sufficient accuracy [14], we manually correct the recognition result of his/her appearance and disappearance.

8.1. Results of Video Segmentation

Below, for each video, we summarize the sequence of intervals of the target character's appearance and disappearance along with the parameter K of our video segmentation method:

- **Star Wars Episode II:** The sequence consists of *305* intervals of *Anakin*'s appearance and disappearance. It is divided into $K = 46$ events.
- **River Runs Through It:** The sequence consists of *437* intervals of *Paul*'s appearance and disappearance. It is divided into $K = 58$ events.
- **Mr. Bean:** The sequence consists of *339* intervals of *Bean*'s appearance and disappearance. It is divided into $K = 51$ events.
- **PSYCHO:** The sequence consists of *475* intervals of *Marion*'s appearance and disappearance. It is divided into $K = 40$ events.

Our video segmentation method divides the above videos into semantically meaningful events with the average accuracy *77%*. We explain some main reasons for this good segmentation result using Figure 4. Figure 4 (a) represents the subsequence of intervals of *Marion*'s appearance and disappearance, which ranges from the *175*-th to the *245*-th interval. Figure 4 (b) represents the subsequence of intervals of *Paul*'s appearance and disappearance, which ranges from the *375*-th to the *435*-th interval. Both of the above subsequences are represented using the bar graph representation. The boundaries between two consecutive events are depicted by the vertical dashed lines. For each event, the horizontal solid line on the positive side represents the mean appearance duration (i.e. $1/\lambda_A^{e_i}$), while the line on the negative side represents the mean disappearance duration (i.e. $1/\lambda_D^{e_i}$).

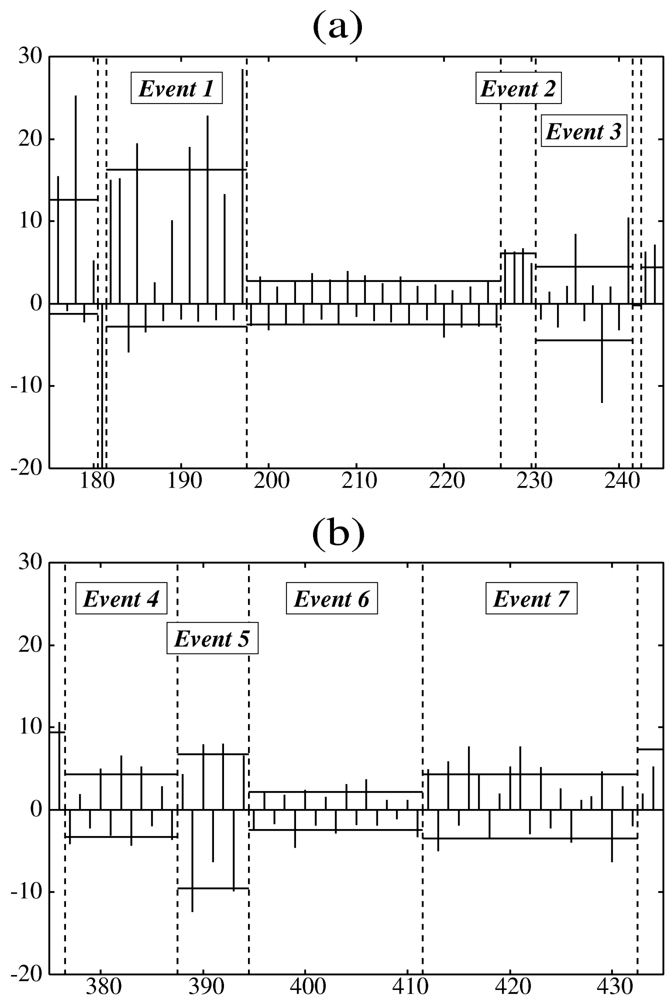

Figure 4. Partial Results for PSYCHO and River Runs Through It

Firstly, our method can robustly detect events based on the probabilistic function in equation (3), so that insignificant changes in appearance and disappearance durations are ignored. For example, in *Event 1* in Figure 4 (a), *Marion* worries about herself, and most of the appearance durations are long except for one short appearance duration. Even for such a noisy duration, our method regards that *Event 1* generally contains long appearance durations.

Secondly, an occurrence ratio between a character's appearance and disappearance can appropriately capture an interaction between him/her and other characters. For example, in *Event 2* in Figure 4 (a), only *Marion* appears and walks around a motel. This event contains no disappearance of *Marion*. But, in *Event 3* where another character comes to *Marion*, her appearance and disappearance occur one after the other. That is, when *Marion* interacts with the other character, the occurrence ratio is accordingly changed.

In addition, appearance and disappearance durations work well to obtain semantically meaningful events. For example, in Figure 4 (b), depending on *Paul*'s appearance and disappearance durations, the intervals from the *377*-th to the *432*-th are divided into four events. Roughly speaking, *Paul* talks to other characters in *Event 4*. And, other characters become to mainly talk in *Event 5*. Thus, *Event 5* is characterized by relatively longer disappearance durations than *Event 4*. Then, in *Event 6*, the conversation between *Paul* and other characters is excited. In this event, *Paul*'s appearance and disappearance quickly switch, that is, appearance and disappearance durations are short. Finally, *Paul* dances with his girlfriend in *Event 7*, which is characterized by relatively long appearance durations. Therefore, each of the experimental videos can be divided into semantically meaningful events with the high accuracy.

8.2. Results of Topic Extraction

From events obtained by our video segmentation method, we extract topics using the burst intensity measure. First, we briefly present topics extracted from *Star Wars Episode II*, *River Runs Through It* and *Mr. Bean*. Due to space limitations, we collect and describe semantically similar topics.

- **Star Wars Episode II:** From *46* events, *26* topics are extracted by setting the threshold of burst intensities to *0.15*. In seven topics, *Anakin* talks to the woman whom he loves. In five topics, *Anakin* chases the enemy using a flying car. He fights enemies in two topics.
- **River Runs Through It:** From *58* events, *20* topics are extracted by setting the threshold of burst intensities to *0.25*. In one topic, *Paul* drops down a river. In two topics, *Paul* fights his brother. In one topic, *Paul* excitedly talks (i.e. *Event 6* in Figure 4 (b)).
- **Mr. Bean:** From *51* events, *19* topics are extracted by setting the threshold of burst intensities to *0.3*. In two topics, *Bean* runs away from police men. In one topic, he rides on a roller coaster. In seven topics, *Bean* performs funny actions.

Now, we closely explain the topic extraction result for *Marion* in *PSYCHO*. Figure 5 present the *14* topics extracted by setting the threshold of burst intensities to *0.3*. In Figure 5, we show which intervals of *PSYCHO* are regarded as topics. Here, each interval between two consecutive vertical lines represents an event, and each shaded interval represents a topic. First, dark-shaded intervals depict topics characterized by bursts of abnormally short appearance durations. For example, *Marion* drives her car in a heavy rain in the *6*-th topic, and she is murdered in the *11*-th, *12*-th and *13*-th topics. Note that topics characterized by bursts of abnormally short appearance durations only cover small intervals of *PSYCHO*. But, these topics consist of many shots relative to their short durations. For instance, the durations of the *11*-th, *12*-th and *13*-th topics are *9.4*, *6.2* and *5.8* seconds, but these topics consist of *12*, *12* and *7* shots.

On the other hand, light-shaded intervals in Figure 5 depict topics characterized by bursts of abnormally long appearance durations. For example, *Marion* makes love with her boyfriend in the *1*-st topic. It is worth noting that the duration of this topic is *104.8* second, but it consists only of two shots. Like this, topics characterized by bursts of abnormally long appearance durations consist of few shots relative to their long durations. Furthermore, such topics include events where only *Marion* appears and her interesting actions are carefully presented by using shots with long durations. For example, *Marion*'s criminal actions are presented in the *2*-nd and *4*-th topics, where the mean appearance durations are *12.1* and *12.6* seconds, respectively. Also, in the case of *Mr. Bean*, these topics describe events where only *Bean* appears and performs funny actions in shots with long durations.

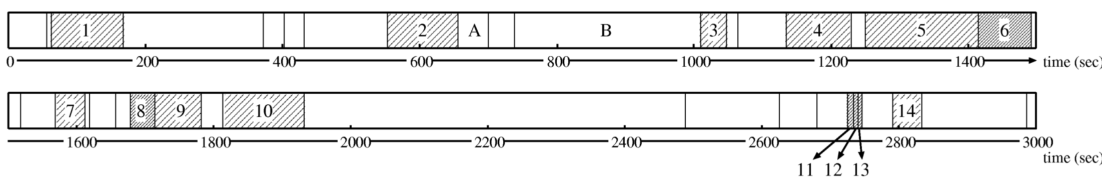

Figure 5. Temporal distribution of extracted topics for Marion in PSYCHO

From the above discussion, if viewers watch the extracted topics, they can roughly understand what kinds of actions the target character performs in a video. Here, watching only topics requires less time than watching the whole video. In the case of *PSYCHO* in Figure 5, the total duration of the *14* extracted topics is *915* seconds, which is much shorter than the total duration of *PSYCHO*, *2986* seconds.

5. Conclusion and Future Works

In this paper, we introduced a novel topic extraction method based on a target character's appearance and disappearance in a video. First, we divide the video into events by applying time series segmentation technique to the sequence of intervals of the target character's appearance and disappearance. In this process, each event is characterized by the pattern of the character's appearance and disappearance and the occurrence ratio. Then, using the burst intensity measure, we extract topics as events which contain one of the following two bursts: the one is characterized by abnormally short appearance durations, and the other is characterized by abnormally long appearance durations. The experimental result verifies that a character's appearance and disappearance are effective for obtaining semantically meaningful events. Also, we show that many interesting topics are extracted, and can be used to develop video abstraction and browsing systems from the perspective of the character. Finally, one of the most important future works is to develop a method which can accurately recognize characters in a video.

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