

# Topic-Based Structuring of a Very Large-Scale News Video Corpus

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## Abstract

We introduce a topic-based inter-video structuring method that considers application to a very large-scale news video corpus as well as user interfaces that provide the users with the ability to efficiently browse through the corpus based on the topic structure. Although the proposed method is a multimedia-integrated method that refers to both text and image based information, this paper focuses on text-based topic segmentation and tracking / threading. First, topic segmentation is performed referring to inter-sentence keyword vector relations within a single video. Next, topic tracking and threading is performed referring to inter-topic keyword vector relations throughout the entire video corpus. Such analysis should reveal the underlying structure of the entire corpus which is not simply a large volume of unrelated data, but data full of rich information in the content-based relational structure itself. The segmentation method evaluated by applying the proposed method showed realistic ability. The proposed method was then applied to 555 daily news video (approximately 270 hours) obtained from a specific Japanese news program. Although detailed evaluation is yet to be done, the user interfaces showed good browsing ability for users to retrieve and track a topic thread of interest.

## Introduction

Due to the recent advance in telecommunication technology, large amounts of videos have become available through various media. Such video data contain a broad range of human activities, which could be considered as valuable cultural and social heritage of the human race. From this viewpoint, news videos contain such information most densely. Nonetheless, building and analyzing a large-scale news video corpus has not been thoroughly examined until recently, due to limitation of computation power and storage size.

Motivated by such background issues, we have built an automatic news video archiving system where important topics can be searched and tracked easily. It automatically records video image, audio, and closed-caption text, and archives them in an Oracle database as shown in Figure 1. Up to now, approximately 270 hours (150GB of MPEG-1 and 925GB of MPEG-2 videos, and 11MB of closed-caption

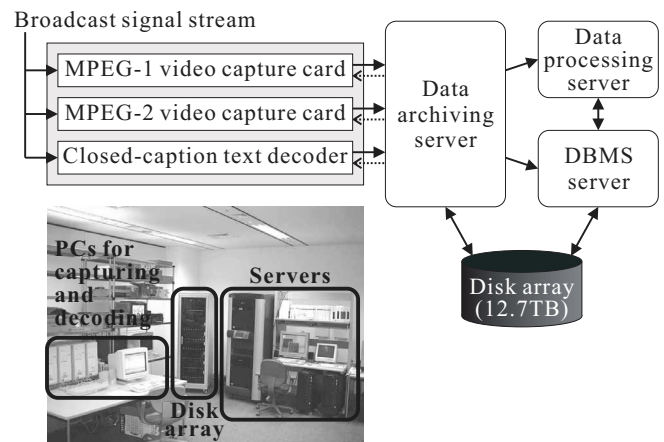


Figure 1: The automatic broadcast video archiving system.

text data) have been obtained and archived from a specific Japanese daily news program.

In this paper, we introduce a topic-based news video corpus structuring method as well as user interfaces that provide the users with the ability to efficiently browse through the corpus based on the topic structure.

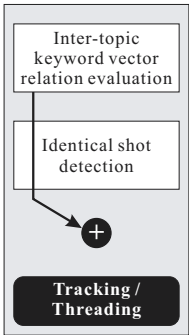
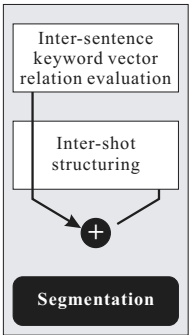
Topic segmentation and tracking is in general a part of the “Topic Detection and Tracking (TDT) task” defined by NIST (National Institute of Standards and Technology 2002). In TDT documents (Wayne 2000), a *topic* is defined as “A seminal *event* or activity, along with all directly related *events* and activities”. Nonetheless, as the term “topic” generally stands for the TDT defined *event* in news video analysis, we will use the term “topic” to indicate an *event* and the term “(topic) thread” a *topic* in this paper.

The overall scheme of the proposed structuring method is shown in Figure 2. First, topic segmentation is performed referring to inter-sentence keyword vector relations and image-based inter-shot structuring within a single video. Next, topic tracking and threading is performed referring to inter-topic keyword vector relations and image-based identical shot detection (Satoh 2002) throughout the entire video corpus. Such integrated media analysis should compensate for the limits of single medium analyses. Note that although the scheme integrates both text and image based informa-

Text / Speech  
(Closed-caption)  
Analysis

Image Analysis

Integration



- Set a window size  $w$ , and evaluate relations between  $w$  preceding and succeeding vectors at each sentence boundary. The relation at the boundary between sentences  $i$  and  $i + 1$  is defined as follows:

$$R_{S,w}(i) = \frac{\sum_{m=i-w+1}^i \vec{k}_S(m) \cdot \sum_{n=i+1}^{i+w} \vec{k}_S(n)}{\left| \sum_{m=i-w+1}^i \vec{k}_S(m) \right| \left| \sum_{n=i+1}^{i+w} \vec{k}_S(n) \right|}$$

$(i = w, w + 1, \dots, i_{max} - w)$

where  $S = \{g, p, l, t\}$  and  $i_{max}$  stands for the number of sentences in a daily closed-caption text. We set  $w = 1, 2, \dots, 10$  in the following experiment<sup>1</sup>.

- Evaluate the following function to detect topic boundaries:

$$R(i) = \sum_{S=\{g,p,l,t\}} a_S \max_w R_{S,w}(i)$$

First, the maximum of  $R_{S,w}(i)$  along the  $w$  axis is taken. According to a preliminary observation, although most boundaries were correctly detected regardless to the window size, there was a large number of over-segmentation. The over-segmentation had the following tendencies:

- Small  $w$ : Tends to over-segment long topics
- Large  $w$ : Tends to over-segment short topics

Thus, taking the maximum should compensate for over-segmentation at various window sizes. An example comparing these tendencies and the effect of taking the maximum is shown in Figure 4.

Next, weighted sum of relations evaluated in separate semantic attributes is defined to evaluate the overall relation. This approach is taken under the assumption that especially in news texts, certain semantic attributes should be more important than others when considering topic segmentation. Multiple linear regression analysis was applied to manually segmented training data (consists of 39 daily closed-caption texts, with 384 boundaries), which resulted in obtaining the following weights:

$$(a_g, a_p, a_l, a_t) = (0.23, 0.21, 0.48, 0.08) \quad (1)$$

The obtained weights indicate that temporal noun sequences are not important in segmentation, and that locational / organizational noun sequences are especially important, which matches with our intuition.

Finally, if  $R(i)$  does not exceed a certain threshold  $\theta_{seg}$ , the boundary between sentences  $i$  and  $i + 1$  is judged as a topic boundary.

Figure 5 shows the process of procedures 3. to 5.

- Create a keyword vector  $\vec{K}_S$  for each detected topic, and re-evaluate the relations between adjoining topics  $i$  and  $j (= i + 1)$  by the following function to concatenate over-segmented topics:

$$R(i, j) = \sum_{S=\{g,p,l,t\}} a_S \frac{\vec{K}_S(i) \cdot \vec{K}_S(j)}{\left| \vec{K}_S(i) \right| \left| \vec{K}_S(j) \right|} \quad (2)$$

<sup>1</sup>The range was set reflecting the fact that 94% of the topics in a manually segmented data ranged from 1 to 10 sentences per topic.

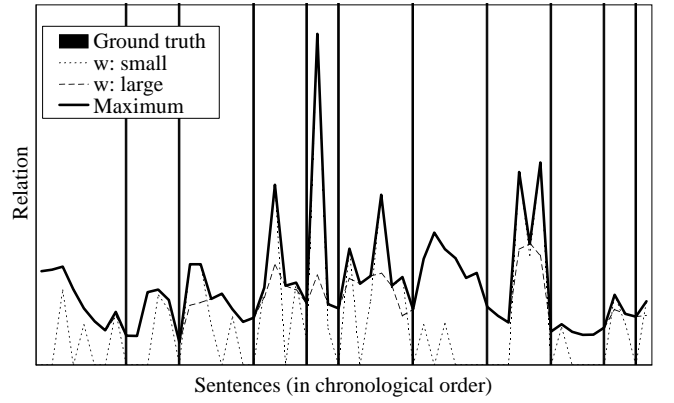


Figure 4: Over-segmentation tendencies according to window sizes.

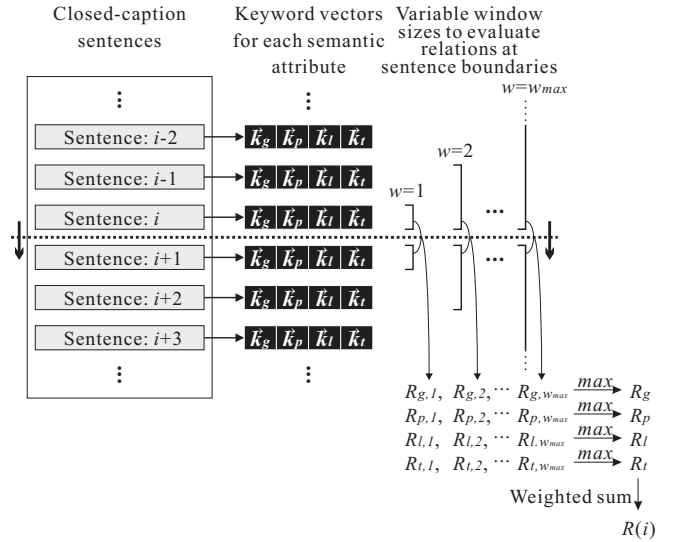


Figure 5: Evaluation of relations at sentence boundaries.

As for  $a_S$ , the same weights as defined in (1) were used. If  $R(i, j)$  does not exceed a certain threshold  $\theta_{cat}$ , the adjoining topics are concatenated. This process is continued until no more concatenation occurs. After the concatenation, topics with only one sentence are excluded since they tend to be either noisy or relatively less important in a large-scale corpus.

Figure 6 shows the recall-precision curb of topic boundary detection derived from applying the proposed method to a test data set (14 days) independent from the training data set. The superiority of employing the weighted segmentation is shown by comparing it with the unweighted segmentation.  $\theta_{seg}$  was defined as 0.17 where the sum of recall and precision of the weighted segmentation curb was maximal. The dotted curb is the recall-precision curb of topic boundary detection after over-segmented topic concatenation when  $\theta_{seg}$  was set to 0.17.  $\theta_{cat}$  was defined as 0.13 where the sum of recall and precision of the concatenated segmentation curb was maximal.

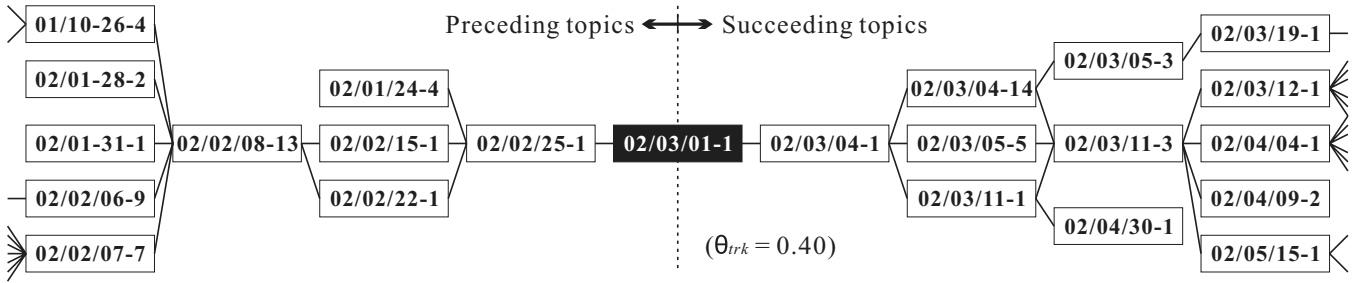


Figure 7: Example of topic threads extracted from the corpus. Topics are named in the following format: “Year/Month/Day-Topic#”. Summaries of actual contents are shown in detail in Figure 11.

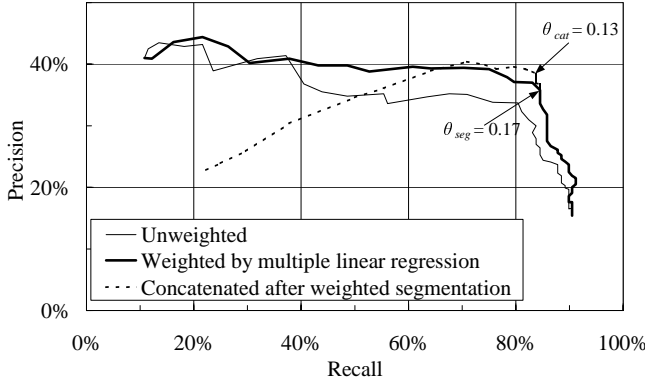


Figure 6: Comparison of segmentation ability, and definition of thresholds from the recall-precision curb.

After defining the thresholds as above, the procedure was applied to 555 daily closed-caption texts ranging from March 16, 2001 to December 13, 2002. This experiment resulted in extracting 6,696 topics with an average of 8.59 sentences per topic, after excluding topics with only one sentence.

We examined the segmentation ability by applying it to the above-mentioned test data set. Excluding topics with only one sentence, there were 130 manually extracted topics as a ground truth. The result is shown in Table 1. Strictly correct topics are those that both the beginning and the ending sentence boundaries completely match with the ground truth, over-segmented topics are those that begin and end within a ground truth topic segment. The proposed weighted method shows higher performance than the unweighted method that does not discriminate semantic attributes. Although strictly evaluated recall and precision is low, if over-segmentation could be accepted, the result could be considered as a realistic ability. Since even over-segmented topics consist of at least two sentences, they should be sufficient to represent the contents of topics to some extent.

**Topic tracking and threading** Topics are tracked and thread structures are analyzed after the segmentation. In order to track topics, relations between any two topic pairs need to be evaluated beforehand. Equation 2 was used for

Table 1: Evaluation of topic segmentation.

	Weighted	Unweighted
Extracted	140	137
(Strictly correct)	47	44
(Over-segmented)	56	53
(Incorrect)	37	40
Overlooked	27	33
Recall (Strict)	36.2%	33.8%
Recall (Accept over-seg.)	79.2%	74.6%
Precision (Strict)	33.6%	32.1%
Precision (Accept over-seg.)	73.6%	70.8%

this purpose, with the same weights as defined in Equation 1.

Topic threads are created by tracking up and down (in chronological order) topic after topic. Only links between topics with weighted relations ( $R(i, j)$ ) larger than a certain threshold ( $\theta_{trk}$ ) are tracked. Figure 7 shows an example of actual topic threads involving topic #1 on March 1, 2002, extracted from the corpus. Only linked topics are considered as related, and topics placed in parallel are considered not related among themselves. The threads are structured so that always the topics linked to the left should be preceding, and those to the right should be succeeding ones. For reference, Figure 11 shows the summaries of actual contents of the topics shown in Figure 7.

### An interactive topic-browsing interface

We implemented a topic browsing interface, namely the “Topic Browser” to provide the users with access to the topics based on the analyzed structure. It consists of two interfaces: the “Topic Finder” and the “Topic Tracker”. Figure 8 shows the “Topic Browser” interface. The left side of the browser displays each interface (inter-switchable by selecting the corresponding tab). The right side displays the video and the closed-caption text corresponding to the topic selected in the tab.

The “Topic Finder” (Figure 9) is a portal to the topic browsing interface. First, a user inputs a query term. Then the interface returns topics that contain the query term in chronological order. Each topic is represented by a thumbnail image (the first frame of the video segment corresponding to the segment) and an excerpt of a closed-caption text.



Figure 8: The “Topic Browser” interface.

A user browses through them and selects the most relevant one to his/her interest to set it as an initial topic for the tracking process.

Next, the “Topic Tracker” (Figure 10) is an interface to track up and down a topic thread interactively. Although the initial topic should be selected through the “Topic Finder”, the consecutive tracking is done solely within this interface. The interface displays relevant topic threads in chronological order, separated in two categories: preceding topics and succeeding topics, reflecting the topic thread structure as exemplified in Figure 7. Here, the terms “preceding” and “succeeding” represent the chronological relations with the selected topic. A user could either track anterior or posterior sequence of topics by selecting one of the presented threads, and setting it as the next selected topic. Such interactive tracking goes on topic after topic. Figure 10 shows the list of topic threads starting with the topic selected in Figure 9. Each thread represents a different subject related to the series of terrorist attacks on September 11 and its aftermath.

The “Topic Finder” may seem somewhat similar to conventional keyword-based news video retrieval, but the combination with the “Topic Tracker” narrows down the result according to the users’ interests and intentions which is important when dealing with a large-scale corpus. On the other hand, while narrowing down the results, the tracking could also be considered as a query expansion process. Having the two seemingly opposite characteristics, the tracking process provides a user with a topic thread that matches their interests and intentions to the maximal extent. Moreover, it reveals chronological transition, divergence, and merger of topic threads, which will be effective for thorough understanding of the story related to the initial query. Figure 12 shows an example of the tracking by one of the authors trying to recall the path to the attack to Afghanistan after the series of terrorist attacks on September 11. We found the above-mentioned features very effective and informative after trying to track down several topics of interest.

Similar approaches are taken in (Christel *et al.* 2002), al-

though they fix the browsing interfaces within individual semantic attributes. On the contrary, our interface is designed to cope flexibly with various and vague interests and intentions of the users.

## Conclusions

In this paper, we proposed a topic-based news video structuring method as a first step to reveal the underlying content-based structure in a very large-scale news video corpus. First, methods to segment and track / thread topics by closed-caption text analysis were described and evaluated. Next, interactive user interfaces that provide the users with the ability to browse the corpus based on topic structure were introduced. Although detailed evaluation is yet to be done, the interface showed good browsing ability for users to retrieve and track a topic thread of interest.

We will further investigate on achieving better topic segmentation quality by referring to image-based video structures to compensate for the limitation of text-based analysis (e.g. lack of distinctive keywords). Topic tracking will be improved by referring to graphically identical shots (Sato 2002). This is based on the assumption that the same video footage is played over and over in news videos discussing the same topic, due to the limitation of data source. Here, we consider to employ identical shots, since current image-based similar shot retrieval technology is not robust enough to retrieve similar contents sufficiently. The tracking interface will also be improved by dynamically adjusting the weights used in Equation 2, depending on the user’s initial query terms and tracking history in a relevance feedback manner. Such adjustment should provide the user with related topics reflecting his/her intention.

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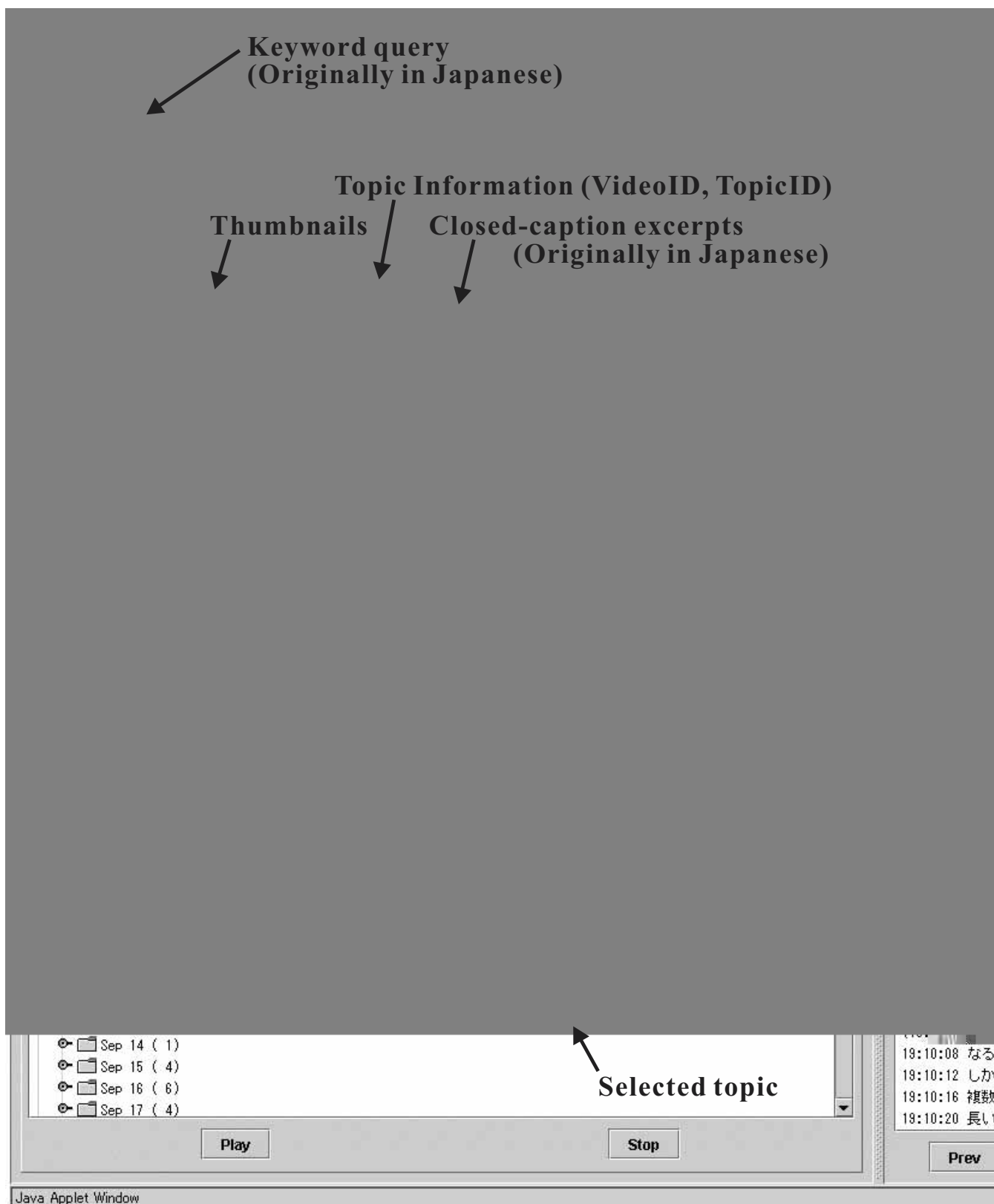


Figure 9: The “Topic Finder” interface. Result of a query “Bin Laden”.



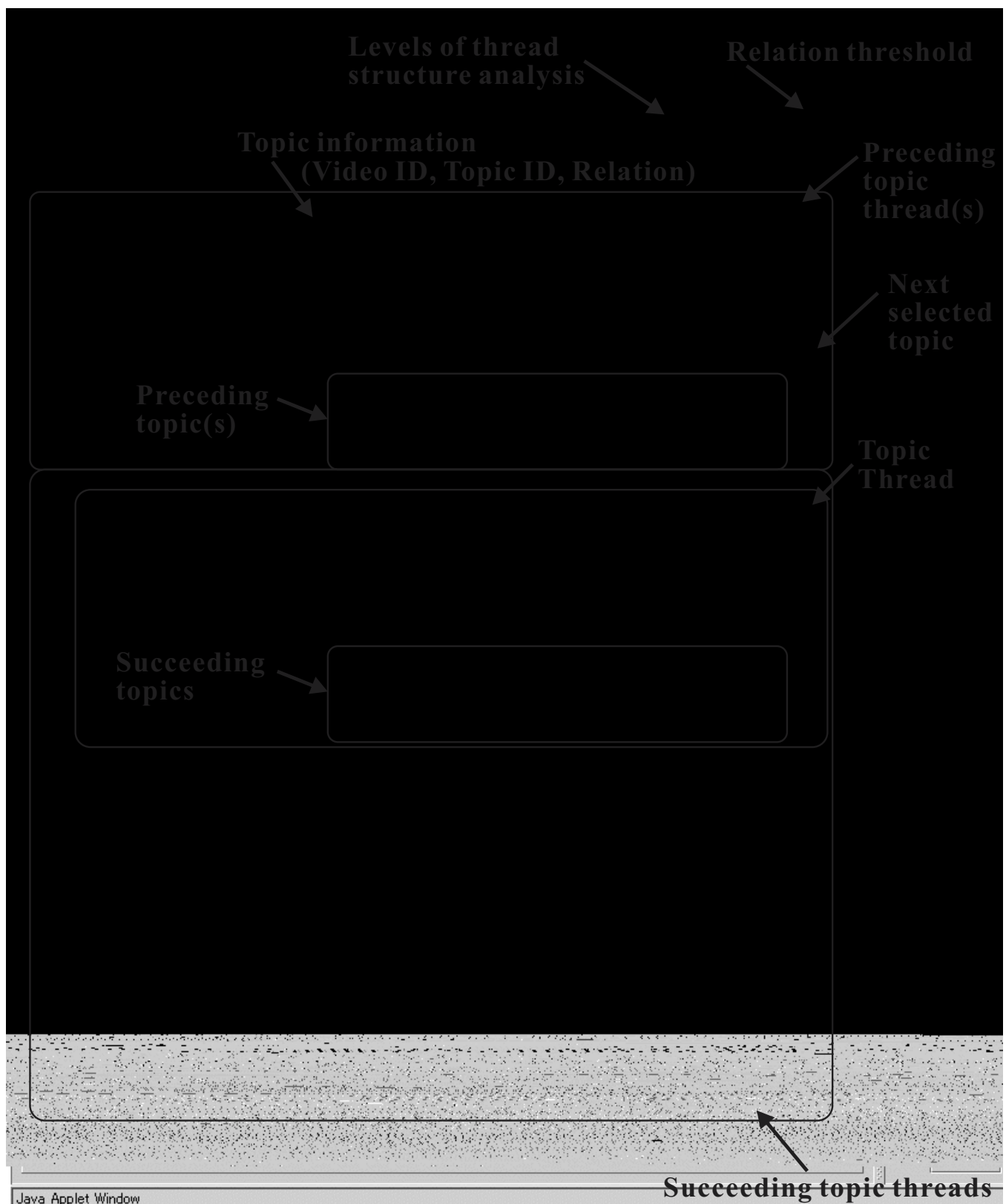


Figure 10: The “Topic Tracker” interface. [Preceding topic(s)] Thread 1: Report on the series of terrorist attacks on September 11. [Succeeding topics] Thread 1: Investigation on the attack; Thread 2: Travel warning by the Ministry of Foreign Affairs; Thread 3: Beginning of Ramadan in Egypt.



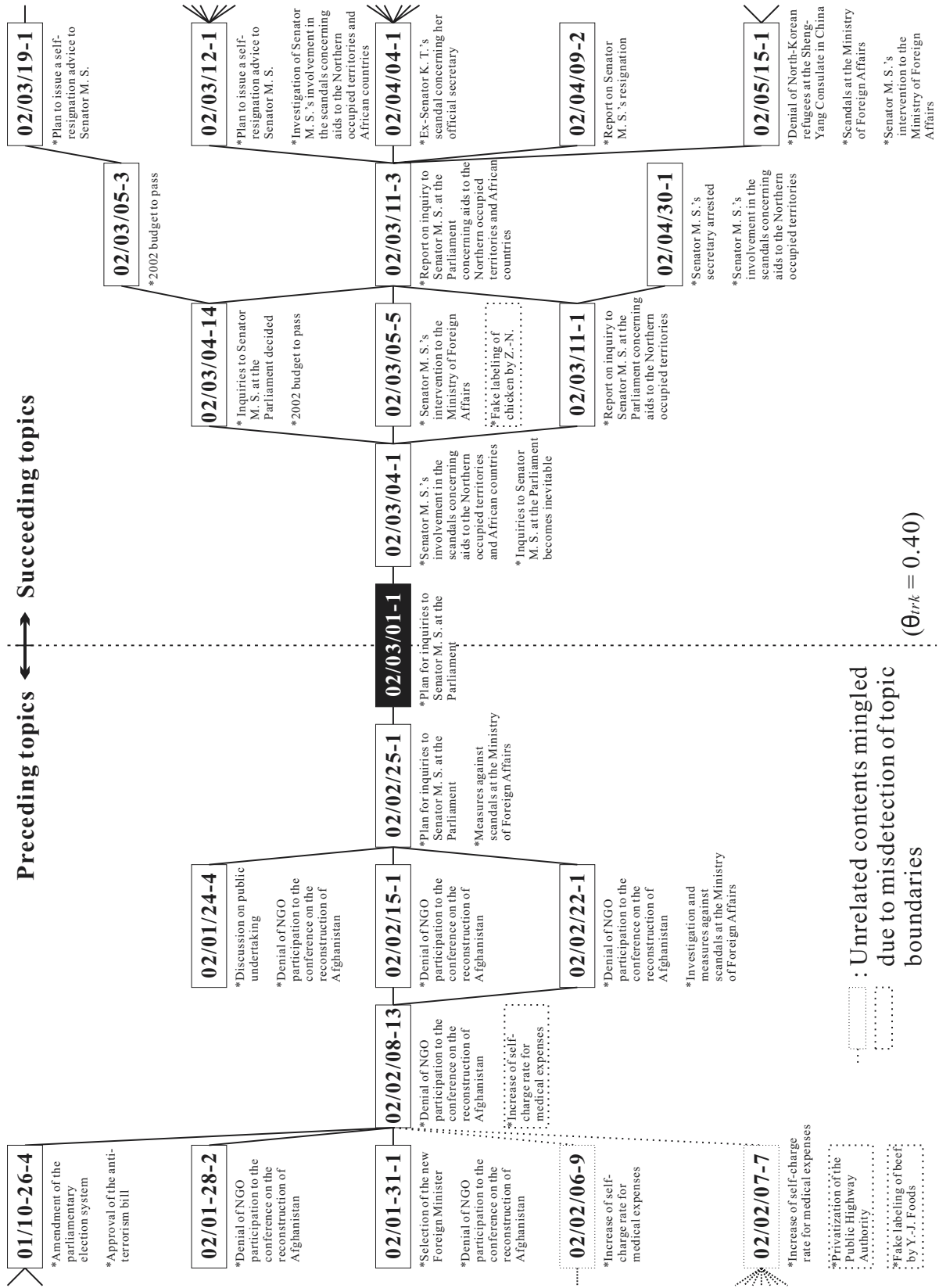


Figure 11: Detailed example of topic threads extracted from the corpus. Topics are named in the following format: “Year/Month/Day-Topic#”.



Figure 12: Detailed example of topic tracking: The thread was selected by one of the authors. Starting from the report on the attack, the process of the investigation and the path to the attack to Afghanistan could be understood.