News Topic Tracking and Re-ranking with Query Expansion Based on Near-Duplicate Detection

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Abstract. Increase of digital storage capacity enabled the creation of large-scale news video archives. To make full use of the archive, it is necessary to grasp the development and dependencies of news stories. Considering this problem, we investigate tracking and re-ranking methodologies of news stories. The archive used as a test-bed consists of more than 30,000 news stories. This paper proposes a novel scheme of mining topic-related stories through a query-expansion algorithm on the basis of near duplicates built on top of text. Experiments showed that the query-expansion algorithm based on near-duplicate constraints outperformed traditional methods that only use textual features.

Keywords: News Topic Tracking, News Topic Re-ranking, Near-Duplicate Detection, Video Data Mining.

1 Introduction

Recent advances in broadband networks, storage devices, and digital video broadcasting has created a demand for large-scale broadcast video databases and intelligent access. Broadcast video, especially news video, contains a broad range of human activities that could be considered as a valuable cultural and social heritage. To make full use of the overwhelming volume of news videos available today, it is necessary to track the development of news stories from different channels, mine their dependencies, and organize them in a semantic way. Among these research efforts, topic tracking is a fundamental step for news browsing, retrieval, topic threading, and summarization. Topic tracking aims at linking together evolving and historical stories according to topics such as *the Trial of Saddam Hussein* and *the 7 July 2005 London bombings*.

Topic tracking is normally studied under the theme of Query by Example (QBE) with textual features as the underlying cues [1,3,4,5,9]. A QBE parser parses the search query, e.g. the text of a full document obtained from web pages or closed-caption of news videos, and looks for keywords. Similar documents are searched for based on these keywords. However, textual information is normally not discriminating enough to distinguish documents of similar but irrelevant topics. For example, a story on *the Trial of Saddam Hussein* was broadcasted on

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Fig. 1. Near duplicates across different stories of two topics. The label under each keyframe is the program name and the airdate. Above: *Trial of Saddam Hussein*. Below: *Fraud allegations of Livedoor*.

2006/11/06 from a Japanese news program FNN SPEAK. The keywords (frequency) parsed from this story include *sentence* (8), *this go-round* (4), *former president Hussein* (3), *president Bush* (3), *United States* (3), and *November 5th* (3). By using these keywords as the query and [3] as the search engine, news stories on irrelevant topics were output as results, including *Sentence of homicidal criminal Yasunori Suzuki*, *United States midterm election*, *Sentence of criminal Miyoko Kawahara*, and *Sentence of homicidal criminal Shizue Tamura*. The reason for this is because the keywords parsed from the search query are limited and not informative enough to represent the characteristics of the corresponding news topic.

In addition to text transcripts, news videos provide richer visual information. In news videos, there are a number of near duplicates, which appear at different times and dates and across various broadcast sources. Near duplicates, by definition, are sets of shots composed of the same video material used several times in different programs or material involving the same scene. These materials possibly differ from each other in terms of video editing or camerawork, as shown in Fig. 1. These near duplicates basically form pairwise equivalent constraints that are useful for bridging evolving news stories across time and sources. For example, the stories with the picture of Saddam Hussein shown in Fig. 1 are highly related, and thus should be identified as the same topic.

Duygulu et al. [2] presented a technique for mining and tracking the repeated sequence of shots based only on near duplicate detection. This work assumes that the coverage, i.e. the percentage of stories that share near duplicates with other stories in the same topic, is sufficient enough for complete and thorough topic tracking. However, this assumption cannot be satisfied with large-scale databases. Zhai et al. [6] linked news stories by combining keyframe matching and textual correlation. Hsu et al. [7] tracked four topics with visual duplicates and semantic concepts, and found that near duplicates significantly improve tracking performance. These two works use near-duplicate and textual information as two independent modalities. Because each modality is processed individually and fusion is based only on the score functions of their processing results, the potential inter-modal relationships between the two modalities are not well explored and thus wasted. Different from these multimodality fusion studies, Wu et al. [10] presented a system built on visual near-duplicate constraints, which are applied on top of text to improve story clustering and mining. This work depends on manual near-duplicate labeling, which is impossible to handle with large-scale databases.

We offer a new perspective by exploring the potential inter-modal relationships derived between near-duplicate and textual information for topic tracking and re-ranking. The main points of discussion include: (1) a novel scheme of mining topic-related stories through tracking and re-ranking on the basis of near-duplicates built on top of text, (2) a proposed simple but effective query-expansion algorithm for improving the representativeness of a search query, and (3) a realistic experiment using a large-scale broadcast video database containing more than 34,000 news stories (compared to around 800 news stories used by Wu et al. [10]).

2 Framework Overview

Our system works on a large-scale broadcast video database. Given a news story used as the search query, the system outputs stories depicting the same topic as the query within the database. Formally, a news story is defined as a semantic segment within a news video, which contains a report depicting a specific topic or incident. A story is described as a group of shots. Each shot is described by a set of representative keyframes and closed-captions. Figure 2 depicts our proposed news topic tracking and re-ranking system.

Initially, candidate news stories similar to the query are searched using a topic-tracking method based only on textual information. The reason that we first use a text-based method before near-duplicate detection is because the latter requires processing of visual information and is computationally far more expensive than processing of textual information. On the other hand, the coverage of near duplicates is normally not sufficient enough for complete and thorough topic tracking compared to textual information. After text-based topic tracking, near duplicates are detected from the set of candidate news stories and used to group stories that share these near duplicates. A query-expansion algorithm is then used to improve the representativeness of the search query based on story groups. Finally, the expanded search query is used to re-rank or re-search news stories depicting the same topic within the database.

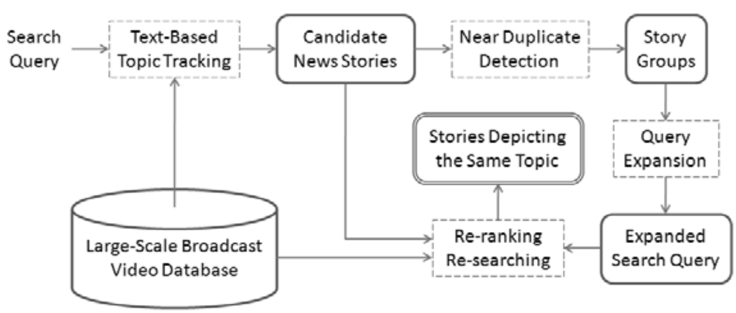

Fig. 2. Proposed news topic tracking and re-ranking system

3 Text-Based Topic Tracking

Topic tracking is normally studied under the theme of Query by Example (QBE) with textual features as the underlying cues [1,3,4,5,9]. In news videos, the focal point or content of evolving stories depicting the same topic normally varies slowly with time. The topic tracking method used in this work should be robust enough over this focal-point variation. In this paper, [3] is used for this purpose, which uses semantic and chronological relation to track the chain of related news stories in the same topic along time. A story boundary is first detected from a closed-caption text broadcasted simultaneously with the video. The resemblances between all combinations of stories are evaluated by adopting cosine similarity between two keyword frequency vectors generated from two news stories. When the resemblance exceeds a threshold, the stories are considered as related and linked. Topic tracking is achieved by considering the children stories related to the search query as new queries to search for new children stories. This procedure forms a simple story link tree, such as the structure in Fig. 3, starting from the story of interest, i.e. the search query. Children stories are defined as news stories related to a parent, under the condition that the time stamps of the children stories always succeed their parent chronologically. The link tree can also be considered as a set of candidate news stories similar to the search query, which is further used for near-duplicate detection.

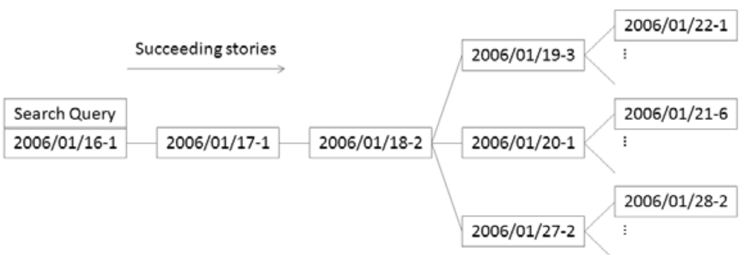

Fig. 3. Example of simple story link structure

4 Near-Duplicate Detection

After text-based topic tracking, near duplicates are detected only from the set of candidate news stories. This can not only dramatically reduce the computation burden due to processing of visual information, but also reduce the probability of potential errors caused by near-duplicate detection. We used an interest-point-based algorithm with a local description for near-duplicate detection. This algorithm was proposed by Ngo et al. [8] and proved to be robust to variations of translation and scaling introduced due to video editing and different camera-work.

They tested their algorithm using a keyframe database instead of a video archive [8]. To extend it to near-duplicate shot detection, we extract multiple keyframes from each video shot. The shot length is equally divided, and the

Fig. 4. Keyframe cropping. (1) Example of keyframe pairs sharing similar video captions but different topics. (2) Crop central part for near duplicate detection.

frames at the points of division are selected as the keyframe. This is to tolerate the variation introduced due to camera and object motion. In equation terms, given the shot length L, the $(i \times L/(N+1))^{\text{th}}$ frames are extracted as the keyframe, where $i = 1 \cdots N$. N indicates the number of keyframes and is empirically set to 3 in this paper.

In news videos, stories of different topics broadcasted from the same news program normally share similar video captions. As shown in Fig. 4 (1), the two keyframes are extracted from stories depicting two different topics but share the same time display (upper left), the same editing pattern (upper right), and similar video captions (below). From our experimental results, we also found a large number of false alarms sharing similar video captions detected as near duplicates. To tolerate this significant impact on the accuracy of near-duplicate detection, we propose to crop the keyframe beforehand. As shown in Fig. 4 (2), only the central part, where there are no video captions, is used for near-duplicate detection.

On the other hand, we also manually excluded anchorperson shots that are not related to the topic while highly possible to be detected as near duplicates. Since anchorperson-shot detection has been extensively studied and many good algorithms were already proposed, this process can be automated if needed.

5 Query Expansion

5.1 Story Grouping

Given a story used as a search query, candidate stories similar to the query are searched across various news programs (Fig. 5). Two stories are linked together if they share at least one pair of near-duplicate keyframes. Stories are then clustered into groups based on these links. Due to the potential errors caused by story segmentation and near-duplicate detection, two stories linked together might not be related to each other. We make the two following assumptions.

Assumption 1: Most stories in the same story group depict the same topic. This assumption is feasible in most cases because near duplicates are detected only from the set of candidate stories similar to the query, so that the probability of potential errors caused by near-duplicate detection is small.

Assumption 2: The largest story group depicts the same topic as the query. This assumption is also feasible because most near duplicates are shared between stories depicting the same topic as the query. From another point of

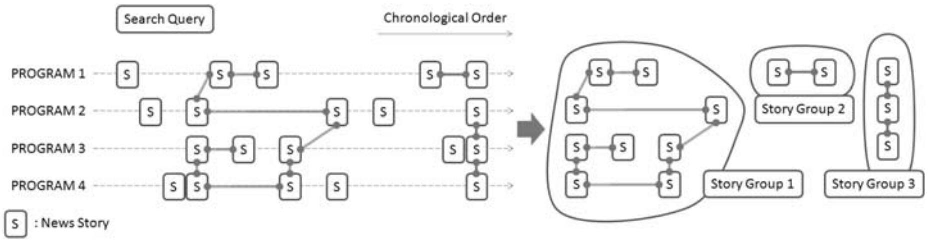

Fig. 5. Group stories sharing near duplicates

Fig. 6. Examples of near-duplicate keyframes depicting *Trial of Saddam Hussein*

view, the noise or outlier topics are normally different from each other so that few near duplicates are shared between them.

The feasibility of these two assumptions is also discussed in Section 6.2. Based on these assumptions, the largest story group is chosen as the expanded query to represent the characteristics of the corresponding news topic that the query depicts. For example, story group 1 shown in Fig. 5 is the largest story group, so it will be used as the expanded query and further processed for keyword weighting. Examples of near-duplicate keyframes within the largest story group depicting *the Trial of Saddam Hussein* are shown in Fig. 6.

5.2 Keyword Weighting

One of the best known schemes for text mining is term frequency-inverse document frequency (*tf-idf*) weighting. We propose a modified *tf-idf* weight and a keyword co-occurrence weight to describe the expanded query. To do so, semantic analysis is first applied to the compound nouns extracted from each story to generate a keyword vector for four semantic classes, *general*, *personal*, *locational/organizational*, and *temporal*. From our experimental results, we found that keywords of the *temporal* class are normally not helpful for identifying news stories depicting the same topic. Therefore, only the compound nouns of the other three classes are used as the keywords.

Different from traditional *tf-idf* weighting schemes, we consider one story group as one document. The story group is denoted as $\mathbb{S}$. Thus, we have the term frequency (tf), defined by Equation 1, where $n(t_i)$ denotes the number of occurrences of the considered keyword t_i in the document. The denominator denotes the sum of occurrences of all keywords in the document.

$$tf(t_i) = \frac{n(t_i)}{\sum_{t_j \in \mathbb{S}} n(t_j)} \tag{1}$$

Table 1. Keywords with six largest *tf-idf*s on *Trial of Saddam Hussein*

Original Query		Expanded Query	
Rank	Keyword	Rank	Keyword
1	*sentence*	1	*former president Hussein*
2	*this go-round*	2	*execution*
3	*former president Hussein*	3	*capital punishment*
4	*president Bush*	4	*Iraq*
5	*United States*	5	*sentence*
6	*November 5th*	6	*Shiah*

The inverse document frequency (*idf*) is a measure of the general importance of the keyword. We consider one story as one document, which is different from Equation. 1. All news stories extracted from 2005/10/19 to 2007/01/19 were used to construct the document corpus for *idf* evaluation. The corpus is denoted as $\mathbb{C}$, and composed of more than 34,000 documents (denoted as s) broadcasted from six different news programs. Thus we have the *idf*, defined by Equation 2, where $|\mathbb{C}|$ denotes the total number of documents in the corpus $\mathbb{C}$. The denominator denotes the number of documents where the keyword t_i appears. The *tf-idf* is then defined by Equation 3.

$$idf(t_i) = \log \frac{|\mathbb{C}|}{|s : t_i \in s, s \in \mathbb{C}|} \tag{2}$$

$$tfidf(t_i) = tf(t_i) \times idf(t_i) \tag{3}$$

As an example, keywords with the six largest *tf-idf*s on *the Trial of Saddam Hussein* are listed in Table 1. We can see that our proposed keyword-weighting algorithm has removed unrelated or potentially ambiguous keywords, e.g. *this go-round*, *president Bush*, *United States*, and *November 5th*, from the original query. On the other hand, keywords more related to the topic, e.g. *Iraq* and *Shiah*, are evaluated with higher importance.

For the keyword co-occurrence weight, we consider one story as one document and one story group as one document corpus. The co-occurrence frequency (cf) of each keyword pair (t_i, t_j) is first evaluated (Equation 4). The numerator denotes the number of documents where both t_i and t_j appear in the document corpus $\mathbb{S}$. $|\mathbb{S}|$ denotes the total number of documents in $\mathbb{S}$. Thus, we have the keyword co-occurrence weight (cw), defined by Equation 5.

$$cf(t_i, t_j, \mathbb{S}) = \frac{|s : t_i \in s, t_j \in s, s \in \mathbb{S}|}{|\mathbb{S}|} \tag{4}$$

$$cw(t_i, t_j, \mathbb{S}) = cf(t_i, t_j, \mathbb{S}) \times idf(t_i) \times idf(t_j) \tag{5}$$

5.3 Text Similarity Based on Expanded Query

For the expanded query or a single story (Section 5.2), a keyword vector $\boldsymbol{V}$ can be created as follows.

$$\boldsymbol{V} = (tfidf(t_1), tfidf(t_2), \cdots, tfidf(t_N)) \tag{6}$$

For expanded query $\mathbb{S}$, we use $\boldsymbol{V}_{\mathbb{S}}$ to denote the vector with N in Equation 6 denoting the number of keywords in $\mathbb{S}$; in the case of story s, $\boldsymbol{V}_s$ denotes the vector with N denoting the number of keywords in this story. The keyword similarity between the expanded query and a story is thus defined by the cosine similarity shown in Equation 7.

$$r_1(\mathbb{S}, s) = \frac{\boldsymbol{V}_{\mathbb{S}} \times \boldsymbol{V}_s}{\|\boldsymbol{V}_{\mathbb{S}}\| \|\boldsymbol{V}_s\|} \tag{7}$$

On the other hand, the keyword co-occurrence similarity between $\mathbb{S}$ and s is defined by Equation 8. Finally, the text similarity between $\mathbb{S}$ and s is defined as the weighted sum of r_1 and r_2 (Equation 9), with $w \in [0, 1]$.

$$r_2(\mathbb{S}, s) = \frac{\sum_{t_i \in s, t_j \in s} cw(t_i, t_j, \mathbb{S})}{\sum_{t_i \in \mathbb{S}, t_j \in \mathbb{S}} cw(t_i, t_j, \mathbb{S})} \tag{8}$$

$$r(\mathbb{S}, s) = w \times r_1(\mathbb{S}, s) + (1 - w) \times r_2(\mathbb{S}, s) \tag{9}$$

6 Experiments

6.1 Database

We tested our system with a large-scale broadcast video database comprised of actual broadcasted videos from 2005/10/19 to 2007/01/19. These videos were broadcasted from six different news programs (FNN SPEAK, NHK NEWS 7, NHK NEWS 9, NHK NEWS 10, NNN NEWS DASH, NNN NEWS PLUS 1) produced by three different Japanese TV stations (Fuji Television, NHK, and Nippon Television). Closed-captions were segmented into stories using the algorithm developed by Ide et al. [3], and videos were segmented into shots by comparing the RGB histograms between adjacent frames. The stories and shots were used as the basic units of analysis. The keywords were derived from a list of compound nouns extracted from closed-captions [3], while the keyframes were derived by equally dividing the shot and selecting the points of division. Note that each shot is represented by three keyframes. The set of near-duplicate keyframe pairs is detected using the algorithm developed by Ngo et al. [8]. The keyframes with the anchorperson has been removed. The database is comprised of 34,279 news stories.

Ten search queries were selected for experimentation, as listed in Table 2, including five Japanese and five foreign news. Candidate stories similar to these queries were searched across the six news programs, and near duplicates were detected from the set of candidate news stories. The duration within which the search was conducted varied from 1 to 15 months. Based on our proposed query-expansion algorithm, experiments on news story re-ranking and re-searching were conducted. Without the official annotation of stories, we built a ground-truth table by manually labeling the result stories of the search according to topic themes.

Table 2. Ten search queries selected for experimentation

Topic Number	Topic	Duration	Domestic / Foreign
T1	*Trial of Saddam Hussein*	15 months	Foreign
T2	*Architectural forgery in Japan*	2 months	Domestic
T3	*Fraud allegations of Livedoor*	2 months	Domestic
T4	*Trial of Saddam Hussein*	2 months	Foreign
T5	*7 July 2005 London bombings*	1 month	Foreign
T6	*Murder of Airi Kinoshita*	1 month	Domestic
T7	*Murder of Yuki Yoshida*	1 month	Domestic
T8	*Murder of Goken Yaneyama*	1 month	Domestic
T9	*2006 North Korean missile test*	1 month	Foreign
T10	*2006 North Korean nuclear test*	1 month	Foreign

6.2 Experimental Results of Story Grouping

Experimental results of story grouping based on the ten search queries are listed in Table 3. From #Story (#TP), we can see that most news stories clustered in the same group depict the same topic as the search query except for T6. In other words, both **Assumption 1** and **Assumption 2** described in Section 5.1 were demonstrated to be feasible in our experiment. For T6, the news topic is on a child abduction-murder that occurred in Hiroshima, and the query story was broadcasted on 2005/12/01. The next day, another child abduction-murder was reported near Tokyo. In most news programs, these two news topics were broadcasted continuously. Due to the high similarity between them, the story segmentation method [3] used in this paper failed to segment them from each other, so that stories of the query topic also contain shots of the noise topic. As a result, stories depicting these two topics were clustered in the same story group based on near-duplicate detection.

Table 3. Experimental results of story grouping. #Candidate: number of candidate stories tracked by the algorithm developed by Ide et al. [3]. #TP: number of relevant stories depicting the same topic as the query. #Group: number of story groups constructed based on near duplicate detection. #Story: number of stories in the story group used for query expansion.

Topic Number	#Candidate (#TP)	#Group	#Story (#TP)
T1	106 (43)	11	9 (9)
T2	370 (174)	3	72 (72)
T3	164 (115)	3	75 (71)
T4	35 (13)	3	10 (10)
T5	93 (64)	1	47 (47)
T6	148 (25)	7	28 (4)
T7	119 (60)	7	26 (22)
T8	35 (34)	3	13 (13)
T9	48 (44)	2	30 (30)
T10	65 (54)	3	39 (38)

6.3 Story Re-ranking

The aim of this section is to justify the performance of our proposed query-expansion algorithm. We evaluate the similarity between each news story tracked using the algorithm developed by Ide et al. [3] and the expanded query using the algorithm proposed in Section 5.3. In Equation 9, w is empirically set to 0.5. These stories are then ranked based on the computed similarity. Normally, stories depicting the same topic as the search query, i.e. relevant stories, should be associated with a higher rank than those depicting similar but irrelevant topics. To evaluate the performance, we compare our algorithm against the baseline algorithm developed by Ide et al. [3]. In this baseline algorithm, the similarity between each news story and the original query is evaluated by adopting the cosine similarity between two keyword frequency vectors generated from them. This similarity is then used for story re-ranking. An evaluation using average precision ($AveP$) was performed using Equation 10, and Fig. 7 illustrates the results. In Equation 10, r denotes the rank, N the number of stories searched, $rel()$ a binary function on the relevance of a given rank, and $P()$ the precision at a given cut-off rank. N_{rel} denotes the number of relevant stories with $N_{rel} \leq N$.

$$AveP = \frac{\sum_{r=1}^{N}(P(r) \times rel(r))}{N_{rel}} \tag{10}$$

From Fig. 7, we can see that our proposed query-expansion algorithm outperformed the baseline for most topics except for T6 and T9. For T6, due to the reason explained in Section 6.2, a large number of stories depicting another different child abduction-murder were associated with higher ranks than relevant stories. T9 is the topic on *the 2006 North Korean missile test* broadcasted from 2006/07/06 to 2006/08/06. The number of noise topics broadcasted during this period, which are different from but similar to the query topic, was small; therefore, both the

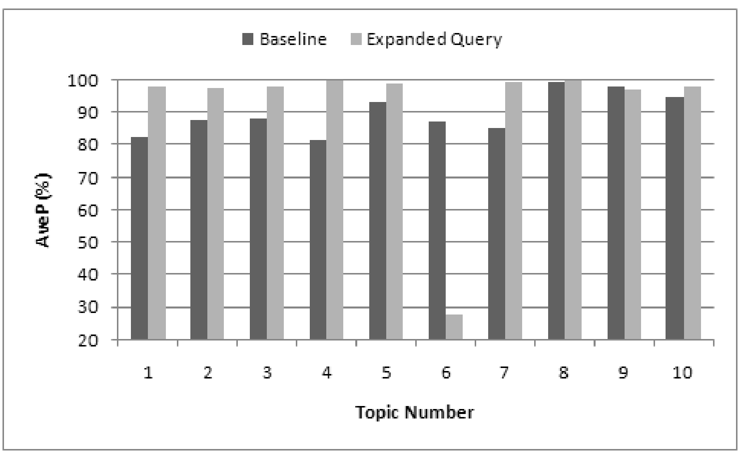

Fig. 7. Average precision comparison for story re-ranking

baseline and our proposed query-expansion algorithm delivered high performance (98.28% for baseline and 97.37% for expanded query).

6.4 Story Re-Searching

This section justifies the searching performance for relevant news stories based on our proposed query-expansion algorithm. In Section 6.3, the similarity is evaluated between only the search query and the stories tracked by [3]. In this section, we evaluate the similarity between the query and all stories broadcasted during the same period as the tracking process. All stories are ranked based on this similarity. Stories with highest ranks are determined as searching results and used for evaluation. The number of results is set to be larger than the number of stories tracked by [3]. The evaluation was conducted in the same way as that described in Section 6.3. Table 4 lists the experimental results.

From Table 4, we can see that when returning the same number of results, the searching process using the expanded query tends to return more relevant stories than the baseline for most topics, especially for T2 and T3. Note that these two queries depict topics on fraud allegations of two Japanese companies, and their broadcast periods were also close to each other. This explains why the baseline returned a large number of irrelevant stories. By using our proposed keyword-weighting algorithm, more representative keywords were associated with higher weights, e.g. *former architect Aneha* and *Huser* (name of a Japanese real estate agency) for T2 compared to *Livedoor* (name of an Internet service provider) and *company president Horie* for T3. On the other hand, our proposed query-expansion algorithm also outperformed the baseline for most topics in terms of average precision, except for T1, T6, and T9.

T1 is the topic on *the Trial of Saddam Hussein* with a duration being 15 months. The original query is more related to the first hearing of Saddam Hussein, while the stories used for query expansion are more related to his execution. During the same period (15 months), a large number of famous criminals all around the world were sentenced to death and stimulated animated discussion

Table 4. Experimental results of story re-searching. #Result1: number of results returned by baseline. #Result2: number of results returned using expanded query. #TP: number of relevant stories depicting same topic as query. $AveP_1$: average precision of baseline. $AveP_2$: average precision of re-searching using expanded query.

Topic Number	#Result1 (#TP)	#Result2 (#TP)	$AveP_1$ (%)	$AveP_2$ (%)
T1	150 (87)	150 (92)	82.55	79.23
T2	400 (186)	400 (355)	79.11	97.11
T3	200 (107)	200 (200)	82.65	100.00
T4	50 (16)	50 (16)	78.24	100.00
T5	100 (77)	100 (93)	93.07	99.04
T6	150 (35)	150 (29)	74.66	24.62
T7	150 (61)	150 (66)	82.02	98.83
T8	50 (36)	50 (46)	96.39	99.95
T9	50 (42)	50 (43)	96.93	96.46
T10	100 (78)	100 (84)	93.35	95.92

on capital punishment. From our experimental results, we found that a large number of false alarms related to these irrelevant trials were determined as relevant stories. This problem was not reflected in Section 6.3 because the tracking process using the original query discarded these irrelevant stories. To justify the effectiveness of our proposed algorithm, we shortened the duration, within which the search was conducted in 2 months (T4). We can see the high performance of T4 from Table 4. For T6 and T9, the reasons of their lower performance are the same as those explained in previous sections.

7 Conclusions

We proposed a novel news topic tracking and re-ranking system. This system offers a new perspective by exploring the potential inter-modal relationships derived between near-duplicate and textual information. A realistic experiment was conducted using a large-scale broadcast video database containing more than 34,000 news stories (compared to around 800 news stories used by Wu et al. [10]). The experimental results showed that our proposed query-expansion algorithm based on near-duplicate detection outperformed traditional QBE methods that only use textual features as underlying cues. In the future, we will investigate the semantic structure of news topics based on video near-duplicate constraints so that we can visualize and summarize stories of a certain topic in a more effective and semantic manner.

References

1. Chieu, H.L., Lee, Y.K.: Query based event extraction along a timeline. In: SIGIR, pp. 425–432 (2004)
2. Duygulu, P., Pan, J.-Y., Forsyth, D.A.: Towards auto-documentary: tracking the evolution of news stories. In: ACM Multimedia, pp. 820–827 (2004)
3. Ide, I., Mo, H., Katayama, N., Satoh, S.: Topic Threading for Structuring a Large-Scale News Video Archive. In: CIVR, pp. 123–131 (2004)
4. Kumar, R., Mahadevan, U., Sivakumar, D.: A graph-theoretic approach to extract storylines from search results. In: Proceedings of the tenth ACM SIGKDD international conference on Knowledge discovery and data mining, pp. 216–225 (2004)
5. Mo, H., Yamagishi, F., Ide, I., Katayama, N., Satoh, S., Sakauchi, M.: Key Image Extraction from a News Video Archive for Visualizing Its Semantic Structure. PCM (1), 650–667 (2004)
6. Zhai, Y., Shah, M.: Tracking news stories across different sources. In: ACM Multimedia, pp. 2–10 (2005)
7. Hsu, W.H., Chang, S.-F.: Topic Tracking Across Broadcast News Videos with Visual Duplicates and Semantic Concepts. In: ICIP, pp. 141–144 (2006)
8. Ngo, C.-W., Zhao, W., Jiang, Y.-G.: Fast tracking of near-duplicate keyframes in broadcast domain with transitivity propagation. In: ACM Multimedia, pp. 845–854 (2006)
9. Lin, F., Liang, C.-H.: Storyline-based summarization for news topic retrospection. Decis. Support Syst. 45, 473–490 (2008)
10. Wu, X., Ngo, C.-W., Hauptmann, A.G.: Multimodal News Story Clustering With Pairwise Visual Near-Duplicate Constraint. IEEE Transactions on Multimedia 10, 188–199 (2008)