A Novel Visualization Method for Distinction of Web News Sentiment

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Abstract. Recently, an increasing number of news websites have come to provide various featured services. However, effective analysis and presentation for distinction of viewpoints among different news sources are limited. We focus on the sentiment aspect of news reporters' viewpoints and propose a system called the *Sentiment Map* for distinguishing the sentiment of news articles and visualizing it on a geographical map based on map zoom control. The proposed system provides more detailed sentiments than conventional sentiment analysis which only considers positive and negative emotions. When a user enters one or more query keywords, the sentiment map not only retrieves news articles related to the concerned topic, but also summarizes sentiment tendencies of Web news based on specific geographical scales. Sentiments can be automatically aggregated at different levels corresponding to the change of map scales. Furthermore, we take into account the aspect of time, and show the variation in sentiment over time. Experimental evaluations conducted by a total of 100 individuals show the sentiment extraction accuracy and the visualization effect of the proposed system are good.

1 Introduction

Recently, the number of online news websites, such as those associated with the Los Angeles Times [1], USA Today [2], and the New York Times [3], has increased with the spread of the Internet. In addition, an increasing number of portal news sites, such as Google News [4], Yahoo! News [5], and MSNBC [6], have been designed to collect and integrate similar news articles from various news sites. These portal sites provide browsing, keyword search, and various personalized services. Users can thus acquire the information they want by accessing a single portal site, instead of several dispersed news sites. Google News [4] is a search engine that searches many of the world's news sources and can aggregate news articles related to a specific topic from different news sites. Yahoo! News [5] allows users to select rankings of news articles based on various aspects, such as readers' comments, blogger attention, and number of bookmarks. MSNBC [6] provides personalization and a customized layout based on the interests of users.

G. Vossen, D.D.E. Long, and J.X. Yu (Eds.): WISE 2009, LNCS 5802, pp. 181–194, 2009.

These existing services are useful. However, there has been little research on distinguishing the viewpoints of different Web sources. News reporters working for different websites may report a same event with different opinions and sentiments. For example, different news sites may support different political parties, so that their opinions on a certain policy proposed by a political party may be in conflict. The results of baseball games are often reported with different sentiments by different newspapers, depending on where the newspaper is based. The present paper examines the effective analysis and differentiation of the viewpoints of different news websites. In particular, we focus on the sentiment aspect.

To solve this problem, we propose a system called the *Sentiment Map*, which can extract and visualize sentiment tendencies for different news websites. When a user enters one or more query keywords, the proposed system first retrieves news articles related to the specified topic, and then calculates sentiment tendencies for each news site using a pre-constructed sentiment dictionary. Finally, the proposed system generates a sentiment map that visually distinguishes the sentiment among different news sites. When users interactively change the scale of the sentiment map, the sentiment tendencies of news articles can automatically be reaggregated for the new geographical scale based on map zoom control. Furthermore, the proposed system also shows the sentiment variation with time. Unlike conventional positive/negative analysis of sentiment, we define more detailed sentiment vectors of four dimensions: Joy $\Leftrightarrow$ Sadness, Acceptance $\Leftrightarrow$ Disgust, Anticipation $\Leftrightarrow$ Surprise, and Fear $\Leftrightarrow$ Anger. The sentiment map helps users acquire an intuitive image of the sentiments of different news sources.

Figure 1 shows an example of a sentiment map for the query "Iraq war", presenting the sentiment distinction at the continent level for this war. This map summarizes the sentiment tendencies of news articles on the topic of the Iraq war based on the unit of each continent. The horizontal axis of each sentiment graph attached to the geographical map represents the period during which news articles are retrieved for the sentiment analysis (In this example, the period is three days from October 5 to October 7, 2008), and the vertical axis represents the average sentiment values of news articles published in each continent. Default presentation of a sentiment graph is positive and negative polarities, averaged by sentiment values of four dimensions. When the mouse moves over a sentiment graph (e.g., North America), more detailed sentiments of four dimensions are separately displayed. Using this sentiment map, a user can obtain a general perspective of the various sentiments held by different continents with respect to the war before further reading the contents of news articles. When the user zooms in to or out of the map, domains (city level, region level, country level, or continent level) are recalculated automatically. Figure 2 shows the sentiment distinction of news articles on the Iraq war at the state level.

The proposed sentiment map enables the following:

- sentiments of news articles beyond positive/negative analysis are extracted
- sentiment tendencies of news sources are distinguished and visualized with different geographical scales
- sentiment variation are shown with respect to time

In the present paper, we describe the concept and implementation of the sentiment map and evaluate the proposed system through several experiments. Section 2 provides an overview of the sentiment map generation. Section 3 describes the offline processing of the proposed system, including the main procedure, the construction of the sentiment dictionary, and the generation of sentiment vectors for news articles. Section 4 describes the online processing. Section 5 discusses the evaluation of the sentiment map conducted by a total of 100 individuals. Section 6 reviews related research. Section 7 concludes the paper and describes areas for future study.

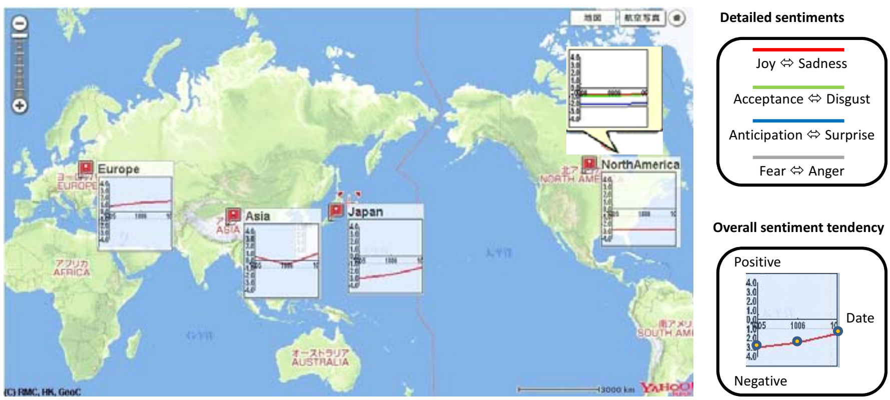

Fig. 1. Example of a sentiment map at the continent level for the query "Iraq war"

Fig. 2. Example of a sentiment map at the state level for the query "Iraq war"

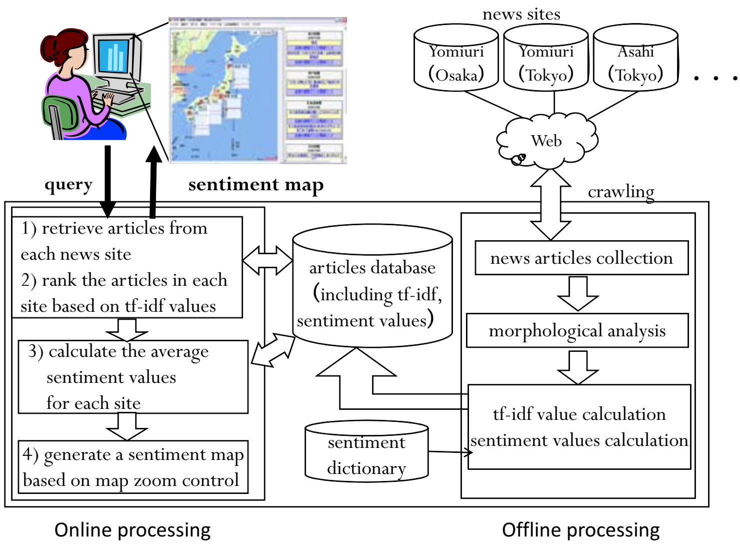

Fig. 3. Flow of sentiment map generation

2 System Overview

Figure 3 shows an overview of the system for generating a sentiment map. This system consists of two parts: offline processing (right-hand side of Figure 3) and online processing (left-hand side of Figure 3).

Collection and analysis of news articles are pre-processed offline, before online retrieval from a user. First, news articles from various news sites are crawled. Then, a morphological analysis of the collected articles is conducted to extract the words with specific parts of speech, and their $tf \cdot idf$ values are calculated. We construct a sentiment dictionary in which the entries include sentiment values of words. A sentiment vector of four dimensions is attached to each news article by looking up the sentiment values of words appearing in the article from the sentiment dictionary and averaging these values. The collected news articles, the $tf \cdot idf$ values of the extracted words, and the sentiment vectors of news articles are stored in a database.

When a user enters one or more query keywords, the proposed system first retrieves relevant news articles from the database. The system then groups the articles by news sites and ranks the articles in each site based on $tf \cdot idf$ values. Then, for each news site, the average sentiment values of news articles are calculated. Next, sentiment graphs are generated for each news site and attached to a geographical map. We call this generated map a sentiment map. The distinction of sentiment tendencies among different news sites can be compared visually. The user can also browse the sentiment summarization at different levels by zooming in to or out of the sentiment map. The proposed system also presents the sentiment variation with time of the news articles for an event.

3 Offline Processing

In preprocessing, news articles are first collected and analyzed as follows:

1. n news articles (P_1, ..., P_i, ..., P_n) are crawled from several specified news sites.
2. HTML tags are eliminated from the crawled news articles.
3. The articles are morphologically analyzed to extract proper nouns, general nouns, adjectives, and verbs.
4. The weight $tf \cdot idf(w, P_i)$ of each extracted word w in news article P_i is calculated:

$$tf \cdot idf(w, P_i) = \frac{C(w, P_i)}{N(P_i)} \cdot log\frac{N}{N(w)}, \tag{1}$$

   where $C(w, P_i)$ is the number of times that word w appears in article P_i, $N(P_i)$ is the number of words extracted from P_i, N is the number of all collected news articles, and $N(w)$ is the number of articles in which word w appears.
5. A sentiment dictionary in which the entries indicate the correspondence of a target word and its sentiment value is constructed.
6. A sentiment vector of four dimensions is generated for each article by averaging the sentiment values of words that appear in the article.

The following sections describe in detail the construction of the sentiment dictionary (step 5) and the generation of sentiment vectors for news articles (step 6).

3.1 Sentiment Dictionary Construction

We consider sentiment values of four dimensions for news articles: Joy ⇔ Sadness, Acceptance ⇔ Disgust, Anticipation ⇔ Surprise, and Fear ⇔ Anger. These four dimensions are designed based on the eight basic elements of human emotion, as proposed by psychologist Plutchik [7]. His theory is one of the most influential approaches for classifying emotion. The issue of comparing it with other models of emotion [8,9] is our future challenge. A sentiment dictionary is constructed to extract the sentiment values of these four dimensions for words by analyzing the Nikkei Newspaper Full Text Database from 1990 to 2001, which consists of two million articles in total. The basic idea is to compare the co-occurrence of target words with two groups of original sentiment words for each dimension. The original sentiment words for the four dimensions are listed in Table 1. Each dimension e ($e \in \{a, b, c, d\}$) has two opposite sets e_1 and e_2 of original sentiment words. For example, for the dimension a of Joy ⇔ Sadness, $a_1 = \{pleasure,\ be\ pleased,\ ...,\ bless\}$ and $a_2 = \{sad,\ feel\ sorry,\ ...,\ sorrow\}$.

Each entry of the sentiment dictionary (Table 2) consists of a target word w and its sentiment values (including a scale value $S_e(w)$ and a weight $M_e(w)$) of four dimensions.

Table 1. Original sentiment words for four dimensions (translated from Japanese)

Dimensions (e)	Original sentiment words ($e_1 \Leftrightarrow e_2$)
a: Joy	pleasure, be pleased, glad, happy, enjoy, blessing, bless
$\Leftrightarrow$ Sadness	$\Leftrightarrow$ sad, feel sorry, sadness, sorrow
b: Acceptance	agreement, agree, consent, acknowledgment, acknowledge, acceptance, accept
$\Leftrightarrow$ Disgust	$\Leftrightarrow$ disgust, dislike, hate, be unpleasant, antipathy, have an antipathy, evasion, evade
c: Anticipation	expectation, expect, anticipation, anticipate, forecast
$\Leftrightarrow$ Surprise	$\Leftrightarrow$ surprise, be surprised, astonishment, astonish, admiration, admire
d: Fear	fear, be scary, misgivings, have misgivings, be frightened
$\Leftrightarrow$ Anger	$\Leftrightarrow$ anger, get angry, resentment, resent, rage, enrage

The scale value $S_e(w)$ of one dimension is calculated using the following procedure. First, considering the Y (year) edition of the Nikkei newspaper, let the number of articles that include any word in the set e of original sentiment words (Table 1) be $df(Y,e)$, and let the number of articles that include both target word w and any word in e be $df(Y,e\&w)$ [1]. The joint probability $P(Y,e\&w)$ of e and w is then calculated as follows:

$$P(Y,e\&w) = \frac{df(Y,e\&w)}{df(Y,e)} \tag{2}$$

Next, considering the two opposite sets e_1 and e_2 of original sentiment words, the interior division ratio $R_{e_1 \Leftrightarrow e_2}(Y,w)$ of $P(Y,e_1\&w)$ and $P(Y,e_2\&w)$ is calculated as follows:

$$R_{e_1 \Leftrightarrow e_2}(Y,w) = \frac{P(Y,e_1\&w)}{P(Y,e_1\&w) + P(Y,e_2\&w)} \tag{3}$$

where $R_{e_1 \Leftrightarrow e_2}(Y,w) = 0$ if the denominator is 0.

Finally, the scale value $S_e(w)$ is calculated as the mean value of all editions,

$$S_e(w) = \sum_{Y=1990}^{2001} R_{e_1 \Leftrightarrow e_2}(Y,w) \Bigg/ \sum_{Y=1990}^{2001} T_{e_1 \Leftrightarrow e_2}(Y,w) \tag{4}$$

where $T_{e_1 \Leftrightarrow e_2}(Y,w)$ is 0 if both $df(Y,e_1\&w)$ and $df(Y,e_2\&w)$ are 0, and $T_{e_1 \Leftrightarrow e_2}$ (Y,w) is 1 otherwise. The introduction of the denominator tends to assign a relatively large $S_e(w)$ to those words that appear only during specific years (rather than every year) but are strongly related to specific sentiment words,

[1] We compared our methods which counted co-occurrence on a document level with those on a paragraph or sentence level in our preliminary experiments. The results showed that the processing time of the methods on a paragraph or sentence level increased dramatically but the improvement of precision was not remarkable. Thus, the document-level co-occurrence was chosen in our current implementation.

e.g., "Olympics". The scale value $S_e(w)$ of a word w is between 0 and 1. This value is close to 1 if w appears in many articles together with the original positive words in e_1, and is close to 0 if w and the original negative words in e_2 often appear in the same articles.

For different words, the numbers of editions in which they appear and the total number of occurrences may vary greatly. Therefore, we introduce the weight $M_e(w)$ of w, which is calculated as follows:

$$M_e(w) = \log_{12} \sum_{Y=1990}^{2001} T_{e_1 \Leftrightarrow e_2}(Y, w) \times \log_{144} \sum_{Y=1990}^{2001} (df(Y, e_1\&w) + df(Y, e_2\&w)) \tag{5}$$

$M_e(w)$ is proportional to the number of editions and the number of occurrence, which means words that appear multiple times and in several editions are assigned large weights. Specifically, the words, $M_e(w)$ of which are 0, are not appended to the sentiment dictionary. Since we use a large corpus, the number of such words is actually small and the coverage of words in the sentiment dictionary is high.

Table 2. Examples of sentiment dictionary entries (translated from Japanese)

	Joy	⇔ Sadness	Acceptance	⇔ Disgust	Anticipation	⇔ Surprise	Fear	⇔ Anger
Entry word w	$S_a(w)$	$M_a(w)$	$S_b(w)$	$M_b(w)$	$S_c(w)$	$M_c(w)$	$S_d(w)$	$M_d(w)$
childcare	0.604	1.273	0.336	1.199	0.285	1.346	0.404	1.105
dispatch	0.531	1.312	0.775	1.625	0.493	1.653	0.549	1.386
get angry	0.274	1.300	0.170	1.179	0.107	1.304	0.021	1.622
ghost	0.395	0.869	0.416	0.617	0.338	0.849	0.793	0.803
new year's present	0.897	0.877	0.516	0.456	0.393	0.877	0.564	0.348
smell	0.485	1.309	0.098	1.205	0.133	1.304	0.469	1.113
strong	0.575	1.270	0.190	1.221	0.397	1.489	0.422	1.159
travel	0.659	1.675	0.442	1.499	0.309	1.737	0.425	1.405

3.2 Sentiment Vector Generation for News Articles

The sentiment vector $O(P)$ of a news article P has the form $(O_a(P)$, $O_b(P)$, $O_c(P)$, $O_d(P))$. Consider P as a set of words extracted from it by the morphological analysis. A sentiment value $O_e(P)$ of article P on dimension e is calculated by averaging and inclining the sentiment values of words that appear in P. The calculation equation, which assigns a sentiment value between 0 and 1 to a news article, is as follows:

$$O_e(P) = \sum_{w \in P} S_e(w) \times |2S_e(w) - 1| \times M_e(w) \Bigg/ \sum_{w \in P} |2S_e(w) - 1| \times M_e(w) \tag{6}$$

where the scale value $S_e(w)$ and weight $M_e(w)$ of each word w that appears in P can be looked up in the sentiment dictionary constructed as described above. Many general words may be independent of the sentiment of the text, and the scale values $S_e(w)$ of these words are approximately 0.5. The $|2S_e(w) - 1|$ term of these words approach 0, so that the effect of the emotionless words is removed.

4 Online Processing

When a user enters one or more query keywords, the proposed system performs the following procedure and returns a sentiment map.

1. The news articles that include the keywords are retrieved from the article database.
2. The retrieved articles are grouped by news sites, and the news articles of each site are ranked in the descending order of the $tf \cdot idf$ values of the query keywords in each news article.
3. Sentiment vectors for each news site are generated by averaging the sentiment vectors of news articles in that site, which are generated as described in Section 3.2.

   Each element of a sentiment vector is a value $\in (0, 1)$. For the symmetry of the sentiment graphs which will be generated in the next step, we normalize it to a value $\in$ (-5, 5) by subtracting 0.5 from it and multiplying the result by 10.
4. Sentiment graphs are generated for each news site based on the sentiment vectors and are attached to a geographical map for the purpose of generating a sentiment map.

   We use a graph creating library JpGraph [10] to generate sentiment graphs for news sites. A sentiment graph corresponds to a summarization of sentiment values of news articles related to the query keyword for a new site. Sentiment graphs for news sites are mapped to news site locations on a geographical map using the Yahoo! Map API [11]. This geographical map with sentiment graphs is referred to as a “sentiment map.”
5. When the user changes the scale of the sentiment map, the geographical scale is recalculated based on map zoom control, and sentiment values are resummarized corresponding to the new scale.

   The presentation scale of the sentiment map can be automatically adjusted based on map control, which includes functions such as zoom in and zoom out. The largest scale of the sentiment map is the world map, and the smallest scale of the sentiment map is a news website. When the sentiment map is presented at the world map level, the sentiment tendencies are aggregated for each continent. When the sentiment map is presented at the Japanese map level, sentiment graphs are generated for each region of Japan (e.g., Kanto area, Kansai area, etc.). When the map scale is zoomed in to the Japanese prefecture level, the sentiment summarization level is the individual news site.

5 Experiments

We implement a prototype [12] of sentiment map that extracts sentiments from news articles and visualizes the sentiments on a geographical map. The collected news sites and their geographical regions are shown in Table 3. Section 5.1 presents the interface of the proposed system. To evaluate our system, 100 individuals are asked to provide their judgments about the accuracy of sentiment extraction (Section 5.2), the effect of visualization (Section 5.3), and some comments on the overall system (Section 5.4).

Table 3. News websites considered in the experiments

Country	Region	Prefecture	News site	URL
Japan	Hokkaido·Tohoku	Hokkaido	Hokkaido Shimbun	http://www.hokkaido-np.co.jp/
		Iwate	Kahoku Online Network	http://www.kahoku.co.jp/
	Kanto·Tokai	Tokyo	Tokyo Web	http://www.tokyo-np.co.jp/
		Aichi	Chunichi Web	http://www.chunichi.co.jp/
	Kinki·Chugoku	Hyogo	Kobe Shimbun	http://www.kobe-np.co.jp/
		Hiroshima	Chugoku Shimbun	http://www.chugoku-np.co.jp/
	Kyushu·Okinawa	Nagasaki	Journal Nagasaki	http://www.nagasaki-np.co.jp/
		Okinawa	Okinawa Times	http://www.okinawatimes.co.jp/
Europe			asahi.com	http://www.asahi.com/international/europe.html
America			asahi.com	http://www.asahi.com/international/namerica.html
Asia			asahi.com	http://www.asahi.com/international/asia.html

5.1 System Interface

Figure 4 shows the interface of the proposed system. News sites from which news articles are collected and the dates on which the news articles were crawled are presented on the initial retrieval page. The user can input one or more query keywords and select the period of news articles that he/she wishes to browse (i.e., to analyze the sentiments thereof).

Figure 5 shows the retrieval result for the query keyword "China" during the period from September 8 to September 10 of 2008. The upper-right frame shows the headlines of the top five news articles, the $tf \cdot idf$ values of the query keyword in which are the highest for each site. By clicking the headlines, the user can browse the contents of corresponding news articles. The lower-right frame displays the sentiment graph of the selected news article, as well as the 10 words with the highest $tf \cdot idf$ values, which tend to represent the topic of the news article. A sentiment graph in the lower-right frame is a bar graph, in which four bars respectively represent four kinds of sentiments of a news article. A sentiment graph in the left frame is a line graph, in which the horizontal axis represents time and the vertical axis represents the average sentiment values of four dimensions for a news site. When the mouse moves over a sentiment graph in the left frame, a sentiment graph with more detailed sentiments of four dimensions is displayed. For a retrieval, a sentiment map at Japanese region level is initially shown respectively for four representative Japanese geographical regions. By zooming in, a sentiment map at the news site level can be regenerated. By zooming out to a world map, the sentiment tendencies can be summarized for each continent.

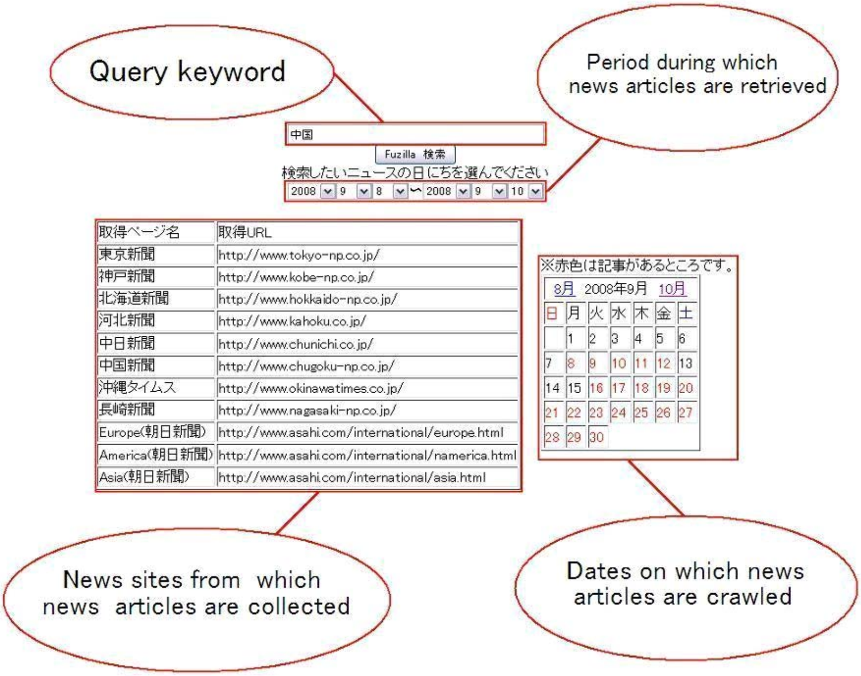

Fig. 4. System interface

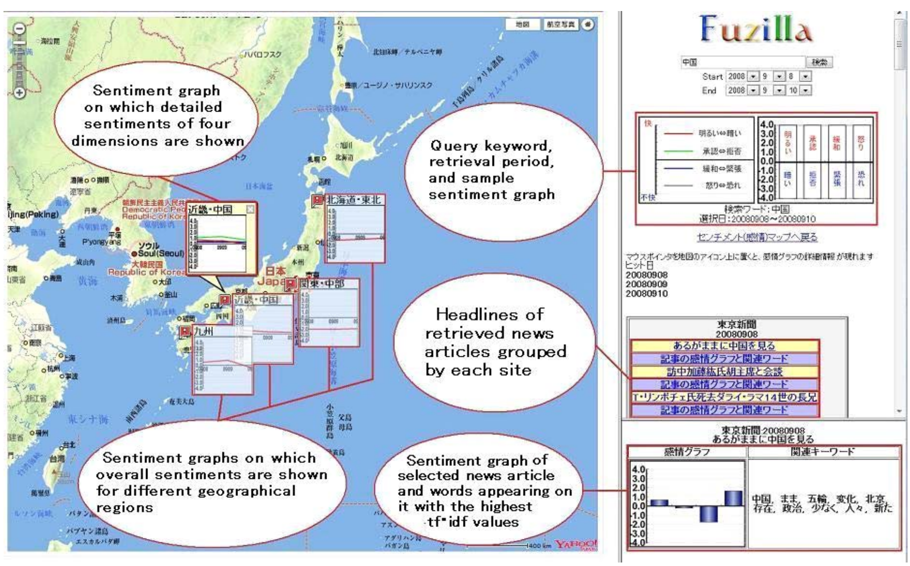

Fig. 5. Retrieval result

5.2 Evaluation of Sentiment Extraction Accuracy

This section reports the accuracy of sentiment values extracted by the proposed system. Given a query keyword, the proposed system retrieves related news articles grouped by each news site, and calculates the sentiment values of four dimensions for each news site by averaging the sentiment values of the 10 news articles with the highest $tf \cdot idf$ values of the query keyword in each news site.

To evaluate the error between the sentiment values calculated by the proposed system and the sentiment values decided by individuals, questionnaires were filled out by 100 individuals. We selected five query keywords and for each keyword selected 10 news articles with the highest $tf \cdot idf$ values in a specific news site. These individuals read the 10 news articles and evaluated the sentiment tendency on four dimensions. For a news article and a dimension, e.g., Joy $\Leftrightarrow$ Sadness, the individuals assigned the news article one of five levels: joy, close to joy, neither joy nor sadness, close to sadness, and sadness. n_1, n_2, n_3, n_4, and n_5 ($\sum_{i=1}^{5} n_i = 100$) were the numbers of the individuals who gave the five levels. We converted the evaluation of the individuals to a numerical value using the following scoring system: joy = 1, close to joy = 0.75, neither joy nor sadness = 0.5, close to sadness = 0.25, and sadness = 0. The sentiment value of a news article on a dimension evaluated by the 100 individuals was $(n_1 * 1 + n_2 * 0.75 + n_3 * 0.5 + n_4 * 0.25 + n_5 * 0)/100$. Finally, the sentiment values of the 10 news articles were averaged as the sentiment values for the news site.

The error of sentiment values between the proposed system and the user evaluation is shown in Table 4. For most of query keywords and most of sentiment dimensions, the sentiment values averaged by the 100 individuals' judgments and those calculated by the proposed system are similar. For example, the sentiment value of the news articles related to the query "Beijing" for the dimension of Joy $\Leftrightarrow$ Sadness which our system calculates is 0.5110, which is a value close to the users' average 0.5203. The average errors of all the query keywords are small, between 0.068 and 0.105, which indicates that the proposed system can extract sentiment values that are similar to those decided by individuals.

Table 4. Evaluation of the error of sentiment values between sentiment values calculated by the proposed system and sentiment values decided by individuals

Query keyword		Average sentiment values of news articles related to the keyword			
		Joy $\Leftrightarrow$ Sadness	Acceptance $\Leftrightarrow$ Disgust	Anticipation $\Leftrightarrow$ Surprise	Fear $\Leftrightarrow$ Anger
Beijing	user	0.5203	0.5815	0.5368	0.5165
	system	0.5110	0.5255	0.3766	0.5566
teacher	user	0.2533	0.3230	0.3528	0.7560
	system	0.4639	0.5135	0.4430	0.4952
Hashimoto governor	user	0.5080	0.5590	0.5115	0.5075
	system	0.4236	0.5244	0.5238	0.4571
Kyoto	user	0.4733	0.5903	0.5135	0.5120
	system	0.5299	0.5440	0.3983	0.5587
Fukuda premier	user	0.4418	0.4825	0.4453	0.5800
	system	0.4208	0.4692	0.4957	0.4519
Average error		0.07638	0.06814	0.08566	0.10522

5.3 Evaluation of Visualization Effect

In this section, we describe the visualization effect about how helpful the sentiment map is to understand the sentiment distinction. A total of 100 individuals also evaluated the visualization effect of the proposed system using the sentiment map. For each of three given query keywords, our system provided the sentiment map which presented the sentiment distinction at three geographical scales: the smallest scale of news sites, larger scale of Japanese geographical regions, and the largest scale of world's continents. The individuals were asked to provide their comprehension level about how conscious they were of the sentiment distinction among the different news sites, among the different regions, or among the different continents. The evaluation was ranked on a five-level scale: understand, somewhat understand, neither clear nor unclear, somewhat unclear, and unclear. Figure 6 shows the evaluation results for the three query keywords and the three geographical scales. The percentage of individuals who indicated that they could "understand" or "somewhat understand" the sentiment map was 40% to 50%, whereas the percentage of individuals who indicated that the sentiment map was "somewhat unclear" or "unclear" was 25% to 35%. This indicates that the proposed sentiment map is useful for clarifying the news sentiments.

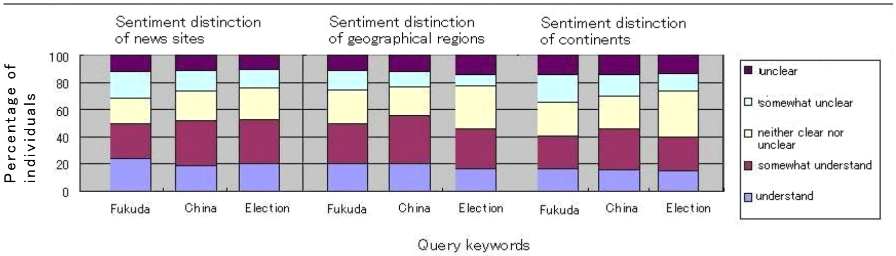

Fig. 6. Evaluation of visualization effect

5.4 Some Comments on the Overall System

A total of 100 individuals were also asked to provide an evaluation of the overall system and arbitrary comments. Individuals, who described the proposed system as being satisfactory, made comments such as, "I became interested in the contents of the news articles and wanted to read them further", and "I could understand the sentiment tendencies of the news sites even without having read the articles". On the other hand, there were also some complaints. For example, dissatisfied individuals reported that the sentiment maps were generated too slowly and that sentiment graphs were sometimes difficult to browse. These aspects will be improved in the future.

6 Related Research

There have been a number of studies on Web news systems, considering information collection, categorization, integration, and recommendation. Google News [4] collects news articles from approximately 4,500 websites and provides similar articles. Yahoo! News [5] uses a ranking technology based on various aspects so that specific types of news are displayed prominently. MSNBC [6] recommends personalized news articles to users by analyzing their browsing history. Although these news sites provide useful services, the aspect of news writer sentiment is not considered.

Sentiment analysis [13,14,15] is increasingly important in the areas of NLP and text mining, which extracts sentiments from text such as movie reviews, book reviews, and production evaluations. Turney [16] proposed a method for classifying reviews into two categories: recommended and not recommended based on mutual information. Pang et al. [17] extracted only the subjective portions of movie reviews and classified them as "thumbs up" or "thumbs down" by applying text-categorization techniques. Esuli et al. [18] presented a method for determining the orientation of subjective terms based on quantitative analysis of the glosses of such terms. However, these methods only consider positive and negative sentiments. Unlike these methods, the proposed method captures more detailed sentiment aspects of four dimensions: Joy ⇔ Sadness, Acceptance ⇔ Disgust, Anticipation ⇔ Surprise, and Fear ⇔ Anger. Furthermore, we visualize the different sentiments of different news sources. Except for the model of emotion proposed by Plutchik [7] which is used by our current research, there also exist other models. Russell [8] proposed a two-dimensional space where the horizontal dimension was pleasure-displeasure, and the vertical dimension was arousal-sleep. The remaining four variables: excitement, depression, contentment, distress, were their combination, not forming independent dimensions. Pitel et al. [9] considered 44 paired emotion directions and created a sentiment dictionary for French using a SVM classifier. Extension based on these models is one of our future work.

7 Conclusions and Future Work

In the present paper, we described a novel method called the Sentiment Map for distinguishing and visualizing the sentiment tendencies of Web news. The proposed method can dynamically summarize the sentiments of news sources for different scales of geographical regions. Sentiment graphs are generated for news sources and are attached to a geographical map, so that users can intuitively distinguish the sentiments of news writers. We implemented a prototype system and, through experimental evaluations, demonstrated that the accuracy of sentiment extraction and the effect of visualization were good.

The proposed method has been applied to analyze the sentiments of news writers. However, research on extracting the sentiments of news readers is also needed, and we plan to construct a system that can recommend news articles that match the sentiments of news readers.

Acknowledgments

This work was supported in part by the National Institute of Information and Communications Technology, Japan, and by the MEXT Grant-in-Aid for Young Scientists (B) (#21700120, Representative:Yukiko Kawai).

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