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16

Reputational Damage to Tourism Industry from Earthquakes – Impact and Analysis of Mass Media Information

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1. Introduction

In the history of Japan, earthquakes have been a frequent occurrence, and some have caused considerable damage. The most recent major earthquake in Japan was the 2011 Tohoku Earthquake, which resulted in unprecedented damage in the country, including damage to a nuclear power plant. When large-scale earthquake disasters occur, direct physical damage to buildings and human causalities are the most visible result. In addition, neighboring tourist areas near the disaster zone receive reputational damage.

Reputational damage is a type of secondary economic damage that is caused following an earthquake when tourists avoid visiting neighboring tourist areas near the disaster zone, even though the tourist areas did not receive serious physical damage. Reputational damage can result in massive economic harm to the tourism industry in neighboring areas. The tourism industry is a key industry that has a major impact on the overall economy and on employment creation. Tourism involves various services such as hotel, restaurant, and transportation services, all of which are deeply related to the primary and secondary industries in the area. Therefore, reputational damage in neighboring tourist areas, not only results in significant economic damage, but also hinders the rapid reconstruction of physical damage in the earthquake-affected area, as the ability of the neighboring area to provide financial assistance and human cooperation to the disaster area is reduced. Currently, reputational damage from earthquakes is important social problem in Japan that must be solved.

However, effective measures to counter reputational damage in neighboring tourist areas have not been established. In academic research, the search for measures to counter reputational damage following earthquakes has been few, although some research on the mechanisms of reputational damage and case studies of past incidences have been conducted (Sekiya, 2003; Sano et al., 2007; Todoroki et al., 2009; Takano & Meguro, 2010). Consequently, people working in the tourism industry must carry out measures following an earthquake such as campaigns to attract customers and sales promotions using trial and error to find the most effective strategies. The establishment of effective measures to counter reputational damage is required immediately.

To establish effective measures to counteract reputational damage, the conditions and trends in information sent by mass media such as newspaper and television must be considered. Media information is an important contributor to the occurrence of reputational damage following an earthquake. Often, a large amount of media information about human causalities and building damage in a disaster area is repeatedly broadcast immediately after an earthquake. Even if measures to counteract reputational damage are performed under such circumstances, they do not work effectively. People do not respond to the measures because the negative media information they have received creates feelings of avoidance toward the neighboring tourist area. However, over time, the amount of media information about earthquake damage lessens and more positive media information such as progress toward recovery in the disaster area begins to be reported by the media. This shift can reduce feelings that the neighboring tourist areas are to be avoided. In this stage, if measures to counter reputational damage are performed, they can be effective because less negative media information exists to influence potential tourists. Thus, careful consideration must be given to the conditions and trends in media information when designing strategies to counter reputational damage following earthquakes.

In this chapter, we discuss the mechanisms by which reputational damage occurs to neighboring tourist areas near earthquake disaster zones (Nagao et al., 2006). In this discussion, we look from the viewpoint of the impact of mass media. Subsequently, we manually analyze the conditions and trends in past media information when reputational damage to neighboring tourist areas have occurred following an earthquake in order to confirm the impact of media information in causing reputational damage (Nagao et al., 2010). Here, we use media information on two earthquakes for the analysis. The first is the 2007 Noto Earthquake and the other is the 2007 Niigata Chuetsu Earthquake. These earthquakes caused serious physical damage to the affected areas, and also resulted in significant economic damage from reputational damage to neighboring tourist areas near the disaster area. We use newspaper and Internet news articles as the target of our investigation. In this analysis, we determine the amount and content of information sent by mass media. Using the results of the analysis, we discuss measures to counteract reputational damage on the basis of the conditions and trends in media information.

Media information changes on a daily basis and must be analyzed immediately to examine its content and identify trends in order to implement measures to counteract reputational damage following earthquakes. It is difficult to perform such information analysis manually because the amount of media information is extremely large when an earthquake occurs. Thus, a method is required that can automatically and accurately analyze media information and then immediately provide the results. We propose an analysis method using information technology (Suto et al., 2009; Nagao et al., 2011). Our method consists of Japanese language morphological analysis, pointwise mutual information/information retrieval (PMI-IR), and so on. The proposed method can analyze the similarity and overall impression in media information to examine content and trends in the data. We apply the proposed method to the media information on the two earthquakes described above in order to confirm its adequacy. Moreover, we discuss an effectiveness of our proposed method by comparing the results of a manual inspection of media information with the result obtained by the proposed method. Finally, from the comparison result, we conclude the potential for measures to counter reputational damage following earthquakes based on the conditions and trends of media information.

2. Reputational damage to the tourism industry

In this section, the details of reputational damage are described, specifically with regards to public concerns and fears about tourist areas near earthquake disaster zones. In addition, the occurrence of reputational damage is explained and the potential countermeasures are discussed.

2.1 Reputational damage

Reputational damage has been originally used as a word related to indemnity problem of economic damage that actually safe food or product is recognized as an object receiving radioactive contamination by nuclear accident and then people do not buy them (Sekiya, 2003). However, in addition to nuclear accident, reputational damage currently expresses the idea that an unrelated or undamaged industry is harmed economically because of fear and suspicion on the part of the public that product or service quality or safety is diminished following an accident or event. Recently, food and industrial products received significant reputational damage following the nuclear accident at Fukushima Daiichi Nuclear Power Plant.

Further, reputational damage to neighboring tourist areas near an earthquake disaster zone recently has been recognized as an important social problem. When earthquake disasters occur, the disaster area incurs physical damage such as human causalities and building collapse, but the neighboring tourist areas that do not receive serious physical damage also receive economic damage from reputational damage. The 2004 Niigata Chuetsu Earthquake is an example of a situation where reputational damage happened in the neighboring tourist areas following an earthquake. In this earthquake, reputational damage occurred to the whole of Niigata prefecture, and then the tourism industry in the prefecture incurred economic damage of about 20 billion Japanese yen. The 2005 Fukuoka Earthquake is another example. In this case, the earthquake reduced the number of tourists in Fukuoka prefecture by 20% compared to normal years.

Japan is situated in an area where many earthquakes occur. Therefore, in comparison with reputational damage generated by nuclear accident or other events, reputational damage from earthquakes has a high possibility of occurring. Moreover, the tourism industry has a very high possibility of receiving reputational damage compared to other industries. Reputational damage results from the characteristic of tourism, namely, that tourism is recreational and not indispensable for living, and even slight worries or fears can result in trip cancelations and avoidance of an area.

Furthermore, the scale of reputational damage in tourism industry is quite large. The tourism industry is an industry that has a strong economic ripple effect on other industries because it consists of various tourism services such as transportation, accommodation, restaurant, and amusement services. In addition, each tourism service is deeply connected to the primary and secondary industries in the region. Reputational damage to the tourism industry near an earthquake disaster zone also influences employment in the area, which can hinder the rapid recovery of the disaster area because the economic damage to the surrounding area limits the ability to provide human and financial cooperation to the disaster area. For these reasons, Japan must find solutions to the problem of reputational damage to tourist areas following an earthquake disaster.

Thus far, however, academic research on reputational damage to tourist area has been not actively performed. The few examples of academic studies have looked at the mechanism of reputational damage, conducted survey investigation in the area where reputational damage has occurred, and analyzed past examples of reputational damage. Moreover, there have been few academic studies on measures to counteract reputational damage. Therefore, when reputational damage occurs to neighboring tourist area, people engaged in the tourism industry must rely on trial and error when performing countermeasures such as public relations and campaigns for tourism.

2.2 Precipitating factors and measures to counter reputational damage

One of major precipitating factors of reputational damage is the information sent by mass media. Reputational damage occurs when mass media sends false or exaggerated information. In addition, reputational damage also can occur even when accurate media information is sent to people. This results from the fact that how receivers of media information respond to information, both true and exaggerated, is itself a cause of reputational damage.

When earthquake disasters occur, information about damage in the disaster area is first sent by the mass media. Serious and disturbing damage in disaster area are repeatedly reported day and night by newspaper, television, radio, and other media. Moreover, in this coverage, the areas with the most serious damage are highlighted. Because of this media focus on the worst hit areas, people incorrectly overestimate the scale of the damage. In addition, although people can approximately ascertain the disaster area, doing so precisely is difficult with only media information. People incorrectly perceive that a wider area than the actual damaged area has received serious damage and is dangerous. Tourist resorts in the area falsely believed to have incurred damage receive reputational damage. Preventing reputational damage is difficult because its causes lie not only in the information sent by mass media but also in the receivers of information. Therefore, countermeasures should be implemented that can effectively limit reputational damage and promote recovery.

To implement effective measures to counter reputational damage, the conditions and trends in media information must be considered, as it is a major factor in causing reputational damage. People feel the need to avoid visiting neighboring tourist areas for sightseeing immediately after an earthquake because media information on damage causes them to overestimate the extent of damage in the wider area around the disaster zone. In such situations, even if strategies such as public relations for tourism promotion are performed, they are not effective. Moreover, people doubt the reliability of information conveyed in these public relations efforts and the measure may have a negative impact. For example, premature measures to counter reputational damage following the 2007 Niigata Chuetsu Earthquake had a negative effect. In this earthquake, a nuclear power plant near the epicenter suffered damage and water containing radiological material flowed from the nuclear power plant into the sea. The mayor undertook a public relations campaign to emphasize that ocean products were harmless. The public relations campaign was performed immediately after the occurrence of earthquake and the damage investigation at the nuclear power plant has not completed yet. For this reason, the public relations efforts had no effect. Moreover, after the campaign, mass media reported many damaged parts and problems at the nuclear power plant. People became suspicious of the discrepancies between the information reported by the mass media and the public relations campaign, and a long-term shift away from the consumption ocean products occurred.

However, over time, the amount of media information about the earthquake decreased and the content of media information shifted from reports of damage to the progress made toward recovery, which eased feelings of avoidance toward visiting the neighboring tourist areas for sightseeing. If the measures to counter reputational damage were performed in this stage, better results could have been expected because there efforts would not have been obstructed by the negative information in the media about earthquake damage. Thus, clarifying the information sent by mass media should be performed and implementation of public relations strategies should be based on the conditions and trends in media information for measure countering reputational damage to be effective.

Against this background, in our research, we analyze media information when earthquake disasters occur. Subsequently, we propose an analysis method of media information using information technologies to automatically analyze media information.

3. Earthquake for media information analysis

In our research, we employ the media information for two earthquakes to perform media information analysis. The details of two earthquakes are described below.

3.1 2007 Noto earthquake

The 2007 Noto Earthquake was a massive earthquake that occurred in Japan on March 25, 2007. The Noto Peninsula is located on the west coast of Japan and projects into the Sea of Japan (See Fig. 1). Almost the entire peninsula is located in Ishikawa prefecture.

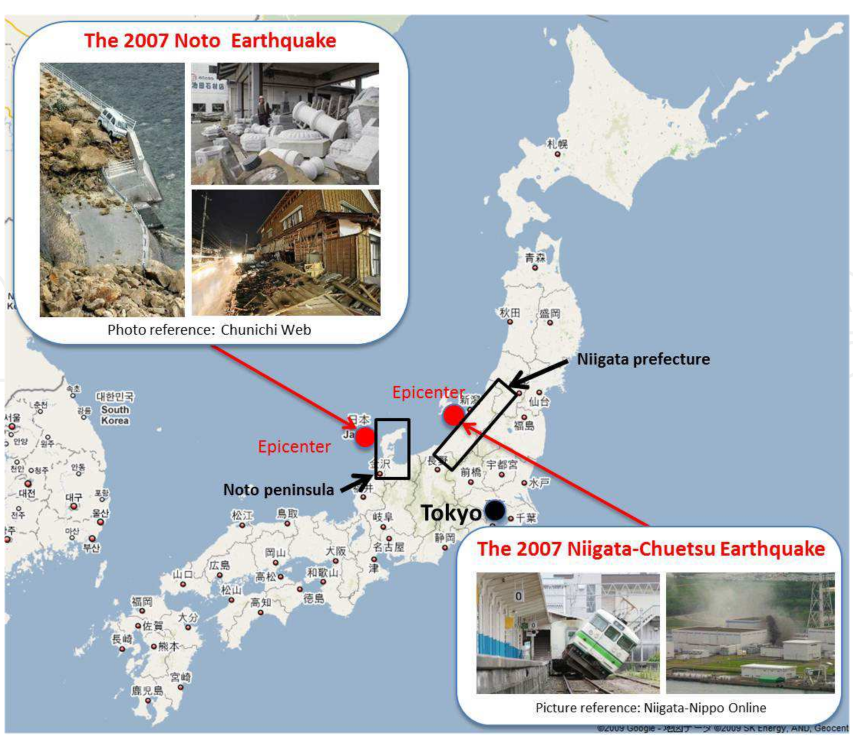

Fig. 1. Location of earthquakes

The epicenter of the earthquake was in the Sea of Japan near the Noto peninsula. The magnitude of the earthquake was estimated at 6.9 on the Richter scale. Shaking in the city of Nanao and the town of Anamizu in Ishikawa prefecture was measured as 6 upper on the Japan Meteorological Agency (JMA) seismic intensity scale. The earthquake caused extensive damage to many cities and towns in Ishikawa prefecture and neighboring Toyama prefecture. In terms of human casualties, one person died and at least 279 people were injured in Ishikawa and Toyama prefectures. In terms of property damage, 649 houses were completely destroyed and 26,614 houses were partly destroyed. Lifeline utilities (electricity, water, gas, etc.) were cut off. In addition, all rail service in this area stopped. Following this earthquake, reputational damage was incurred by many tourist areas in Ishikawa prefecture. For example, at the Wakura Hot Spring Resort in Ishikawa prefecture, 66,413 hotel bookings were cancelled during the month following the earthquake. Wajima city in Ishikawa prefecture had 15,526 hotel booking cancelations. Moreover, the tourism-related sales decreased by 20% in the resorts at Kaga Hot Spring in Ishikawa prefecture, which received almost no physical damage and is far from the epicenter.

3.2 2007 Niigata Chuetsu earthquake

The 2007 Niigata Chuetsu Earthquake occurred on July 16, 2007. Niigata prefecture is located on the western side of Japan along the Sea of Japan (See Fig. 1). Chuetsu is the central area of the three mainland areas of Niigata prefecture. The epicenter of the earthquake was in the Sea of Japan off the coast of Chuetsu. The magnitude of the earthquake was estimated at 6.8 on the Richter scale. Kashiwazaki city, Nagaoka city, and Kariwa village registered the highest seismic intensity, registering 6 upper on the JMA scale. Fifteen deaths and at least 2,315 injuries were reported. In addition, 1,319 buildings were completely destroyed and 40,280 buildings were partly destroyed. Lifeline utilities and various transport facilities were disrupted. Considerable damage resulted from this earthquake and several incidents occurred at the Kashiwazaki-Kariya Nuclear Power Plant. A fire broke out in an electrical transformer and radioactive gases leaked from the nuclear power plant. Many tourist areas in Niigata prefecture experienced significant reputational damage as a result of the public's fears concerning the plant accident. For example, the number of hotel guests in all hot spring resorts in Niigata prefecture was reported to decrease by 40%.

4. Analysis of media information

We analyze the information sent by mass media following the two earthquakes described above in order to investigate the actual condition of the media information. The analysis method and result are described below.

4.1 Analysis method

We collected the information on the earthquakes from two types of media — print newspapers and Internet news websites managed by newspaper publishing companies (henceforth, described as web news). For each earthquake, we collected earthquake-related articles from five newspapers, including four national newspapers and one local newspaper. In the analysis of web news, we used two websites for the 2007 Noto Earthquake and three websites for the 2007 Niigata Chuetsu Earthquake, respectively. For the 2007 Noto Earthquake, articles were taken from Chunichi Web (www.chunichi.co.jp) and Yomiuri Online (www.yomiuri.co.jp).

For the 2007 Niigata Chuetsu Earthquake, we collected earthquake-related articles from MSN Sankei News (sankei.jp.msn.com), Niigata-Nippo Online (www.niigata-nippo.co.jp) and YOMIURI Online. Yomiuri Online and MSN Sankei News are managed by national newspaper publishing companies in Japan, and Chunichi Web and Niigata-Nippo Online are managed by local newspaper publishing companies. In this collection, we treated articles including the name of the earthquake as the disaster-related information. The collection period was two months from the day of the occurrence of each earthquake.

We investigated the amount of information in newspapers and web news. To determine the amount of information, we used the amount of page space of earthquake-related articles for printed newspaper and the number of articles for web news. Moreover, we analyzed the contents of articles collected from both media. In this content analysis, we classified the articles into three categories on the basis of whether or not the article gave readers the feelings of avoidance toward visiting neighboring tourist resorts for sightseeing. The articles that prompted feelings of avoidance were classified into the NEGATIVE category. For example, articles that gave damage reports, the number of deaths, and the like were classified in this category. Articles that ease feelings of avoidance were classified into the POSITIVE category. This category included the articles about the progress of recovery, visits of celebrities, and similar topics. Finally, the articles that neither caused nor eased feelings of avoidance were classified into the NEUTRAL category. The articles reported on topics such as the economic and political changes related to the earthquake were included in this category.

4.2 Analysis results

The analysis results are shown in Fig. 2 through Fig. 5. Figure 2 and Fig. 4 indicate the change in the amount of earthquake-related information in newspapers and web news, respectively, for the two earthquakes. Fig. 3 and Fig. 5 represent the change in the content ratio in each category for newspaper and web news, respectively.

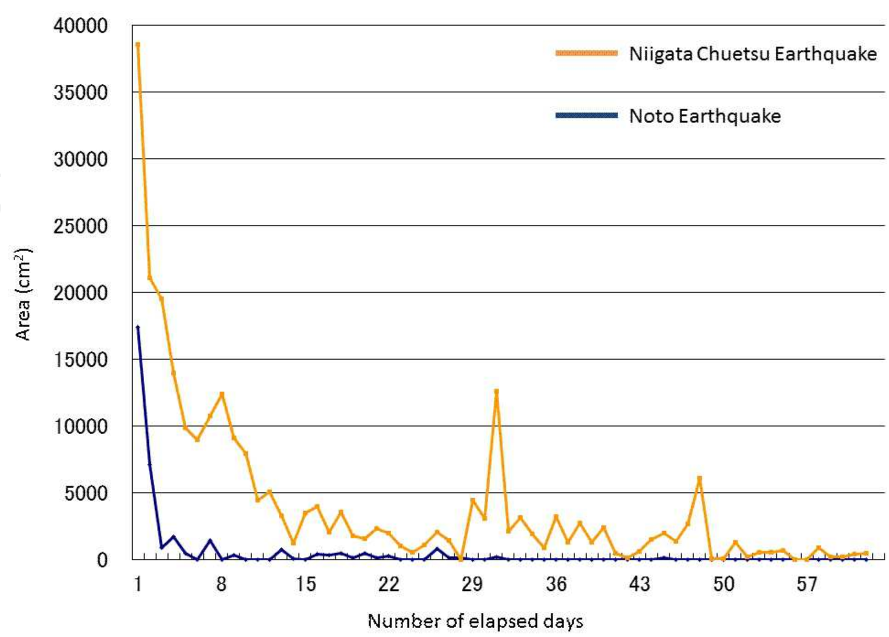

Fig. 2. Amount of earthquake-related information in newspapers

In Fig. 2 and Fig. 4, the x-axis represents the number of days elapsed after the earthquake and y-axis represents the amount of information. For newspapers (Fig. 2), the amount of information represents total amount of page space of articles published by the five newspapers. For web news, the amount of information reflects the average number of articles published on websites (Fig. 4). In Fig. 3 and Fig. 5, the top graph indicates the results of the content analysis of articles covering the 2007 Noto Earthquake and the bottom graph indicates the results for the 2007 Niigata Chuetsu Earthquake. In these figures, the x-axis represents the number of days elapsed after the earthquake and the y-axis represents the content ratio in each category. In these charts, the value at the top of the dark bar represents the ratio of NEGATIVE articles and the value of bottom of dark bar represents the ratio of POSITIVE articles, respectively. When the bar is light-colored, the type of content is reversed, with the ratio of POSITIVE articles at the top and NEGATIVE news at the bottom.

First, we discuss the analysis result for newspaper. As shown in Fig. 2, the amount of information on the Noto Earthquake rapidly decreased following the third day after the earthquake, and the amount of information did not increase after this. In the case of the Noto Earthquake, property damage happened over a wide area, but few people died. It is likely that the amount of information decreased because of a lack of fresh news. In the case of Niigata Chuetsu Earthquake, the amount of information dropped steadily over the first week and then increased during the second week. After the first month, the amount of information increased again. After this, the amount of information did not increase, except for an upward tick on the 48th day after the earthquake. This increase after the 48th day resulted because of the tourism public relations advertisements published by government and is an exception to the general trend in newspaper coverage. For this earthquake, prolonged coverage was performed, likely because this earthquake caused unique damage (e.g., the accident in nuclear power plant and stoppage of automobile manufacturing) that had negative impacts on other areas. To compare the two results, when news coverage extended over a long period of time, the summary of the events of the earthquake disaster was reported. In addition, the results show that the continuity of coverage depends on the scale and features of the damage from the earthquake.

In Fig. 3, the content of newspaper articles on the Noto Earthquake can be divided into three periods on the basis of the ratio between the three categories. The first period is from the day of the earthquake through one week after. The second period is between one and about four weeks after the earthquake. The final period is the period more than four weeks from the occurrence. In the first period, the ratio of NEGATIVE articles was continuously high. In the second period, the ratio of POSITIVE articles increased on some days and the ratios of NEGATIVE articles varied. In the final period, the content fell solely into the NEUTRAL category. The result of the content analysis can also be divided into three periods for the Niigata Chuetsu Earthquake. The first period is from the date of the earthquake until 30 days after. The second period is from 30 days to 40 days after the earthquake. The final period is more than 40 days after the earthquake. In the first period, the ratio of NEGATIVE articles was consistently high. In the second period, the ratio of NEGATIVE category decreased. In the third period, the content ratio for each category showed large variation.

We use the results above to discuss the conditions and trends of media information from the viewpoint of countering reputational damage in surrounding areas. It is obvious that the appropriate period to start measures to counter for reputational damage is during calm periods in terms of both the amount and content of media information. In regard to the content of media information, we regarded calm periods as when the ratio of NEGATIVE articles is low and the ratio of POSITIVE articles begins to rise. This calm period was identified with consideration of the continuity of the ratios for each category. In the analysis results for newspapers, it was found that the appropriate period for measures to counter reputational damage depended on the calm period in terms of content. Therefore, the calm period was four weeks after the Noto Earthquake, and was about six weeks after the Niigata Chuetsu Earthquake, respectively.

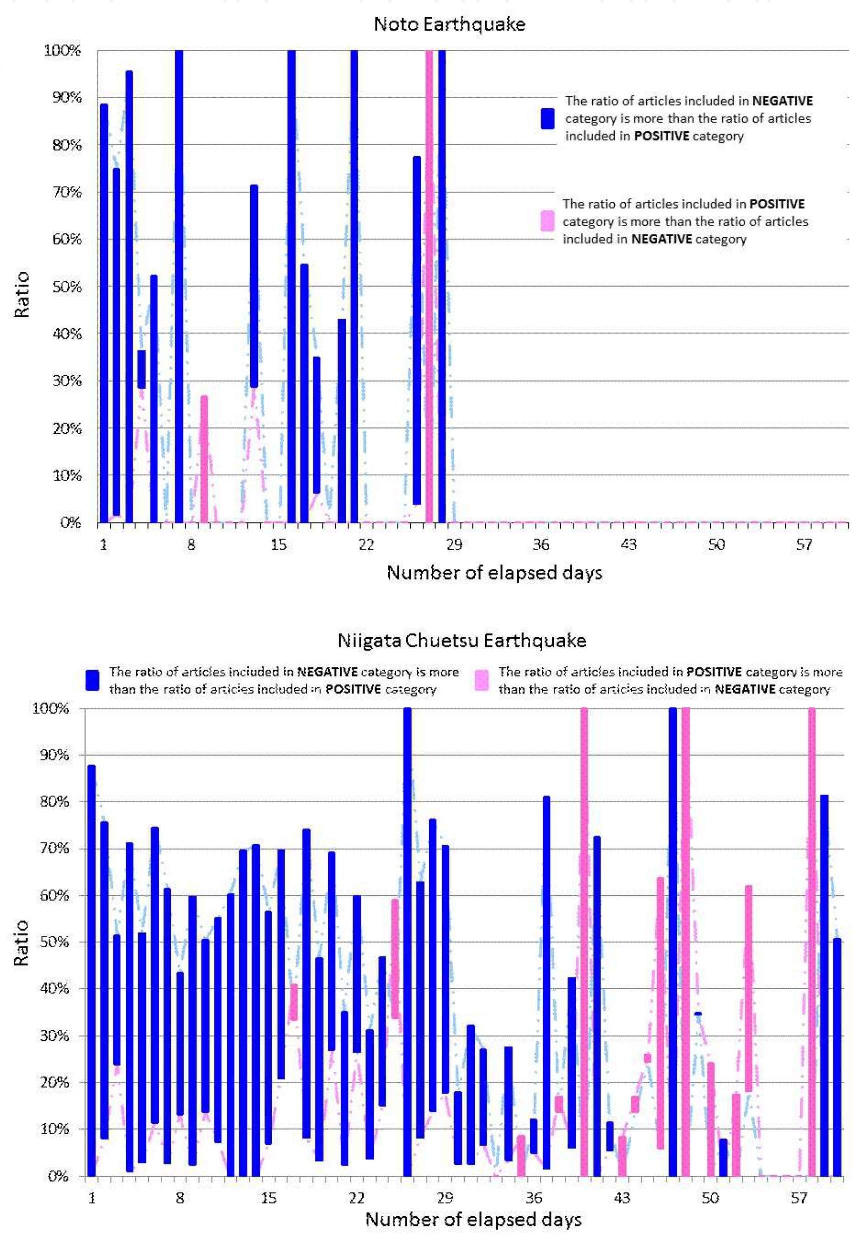

Fig. 3. Results of content analysis of newspapers

Next, we discuss the results of the analysis of web news. Figure 4 shows the change in the amount of information for web news over time. The maximum amount of information emerged on day following the both earthquakes, which reflects the time that is required to confirm the total damage done by earthquake. Although web news can be quickly posted on the Internet, the maximum value emerged on the next day following the earthquake because it took time to investigate the totality of the damage situation, given that these earthquakes caused damage over large areas. The subsequent slow decrease in web news could be found for both earthquakes although the trend in the amount information in two earthquakes differs over the first two weeks after the earthquake. This overall trend and the amount of information means that web news reach a calm period after two weeks following the earthquake

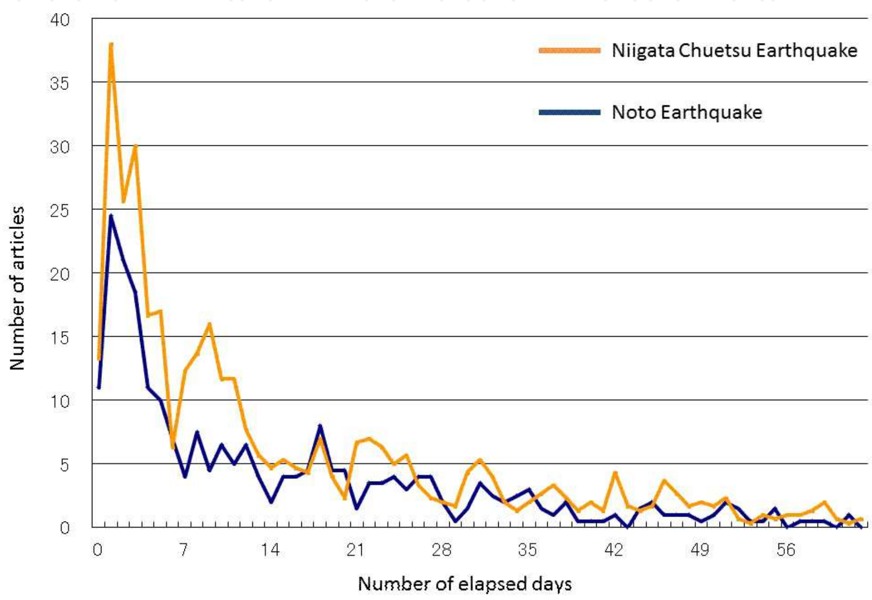

Fig. 4. Amount of information in web news

In Fig. 5, the calm period in terms of web news content is regarded as when the ratio of NEGATIVE articles is low and the ratio of POSITIVE articles begins to rise. This period corresponds to the period two weeks after the Noto Earthquake. For the Niigata Chuetsu Earthquake, it was about four weeks later. The appropriate period for measures to counteract reputational damage from web news corresponds with the calm period of content of media information in common with the results for newspaper.

Figure 6 summarizes the results for the appropriate period to conduct measures to counteract reputational damage after the two earthquakes. We discuss methods to counter reputational damage from each media on the basis of the analysis results. For newspaper, a large amount of page space dedicated to a story attracts readers' attention, and typically it is difficult for an article to be published if it is not topical. Therefore, to be effective, countermeasures using newspapers should include the placement of public relations advertisements that have a wide enough area to attract a great deal of attention during the calm period of media information. Advertising activity during the calm period influences people without being obstructed by media information that gives negative impressions about visiting neighboring tourist areas for sightseeing. Then the countermeasure can begin to remove negative impressions and build positive impressions about tourism in the areas near the earthquake zone. Moreover, such a strategy is expected to effect people of all ages because newspapers are read by many types of people.

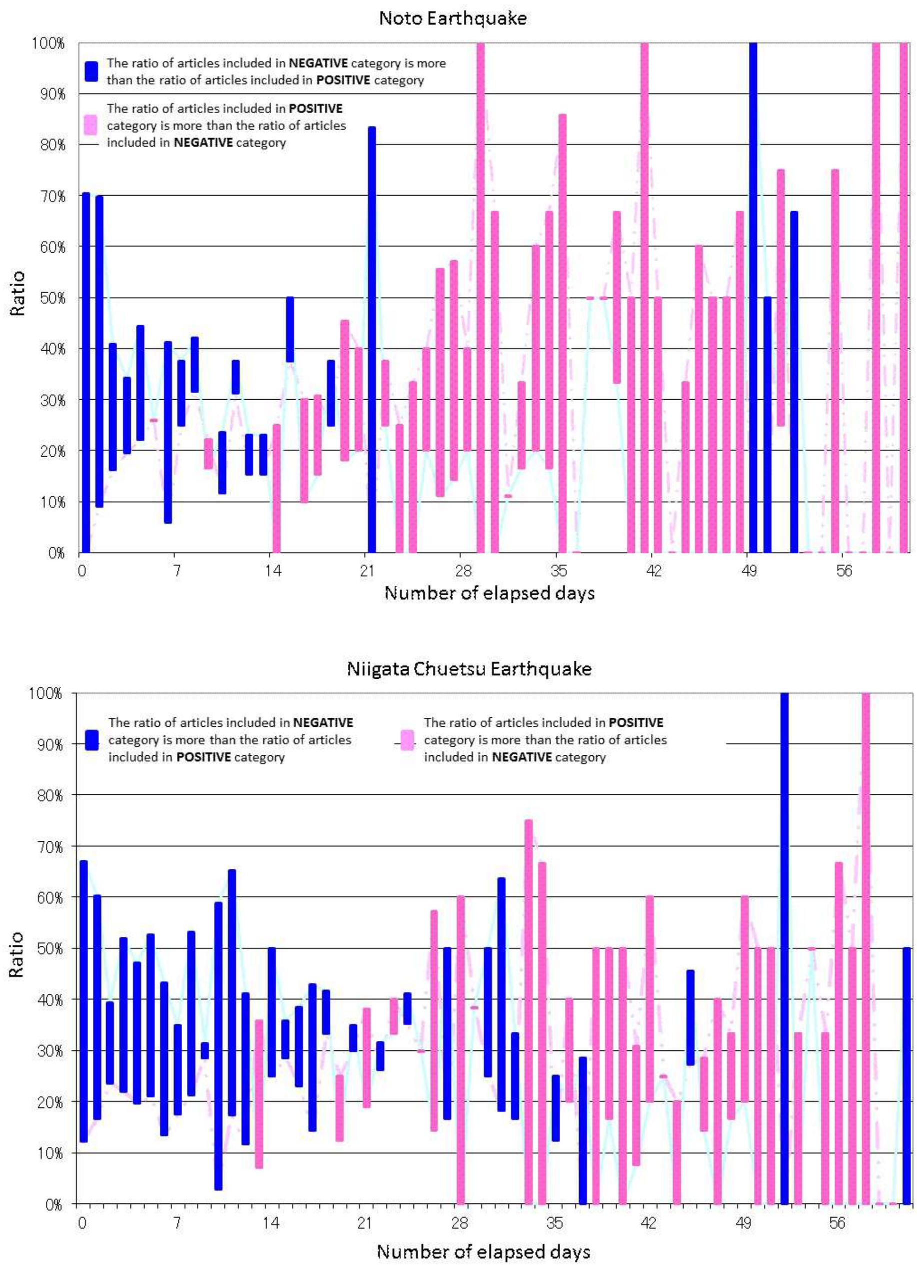

Fig. 5. Results of content analysis of web news

For web news, articles about events and affairs are published even if they are not highly topical. In addition, articles are published promptly on the website. Therefore, a strategy of active public relations measures during the calm period of media information is an effective method to counter reputational damage from web news. By performing such measures, the effect of the public relations efforts can be obtained first, and then the ripple effects from the publication of the web news articles can be expected.

Moreover, reputational damage from earthquake is specifically connected with the effects of potential visitors hesitating to go sightseeing near the disaster area even if it is safe. Therefore, the public relations campaign must clarify that visiting neighboring tourist areas for sightseeing contributes to the smooth rehabilitation of the disaster area.

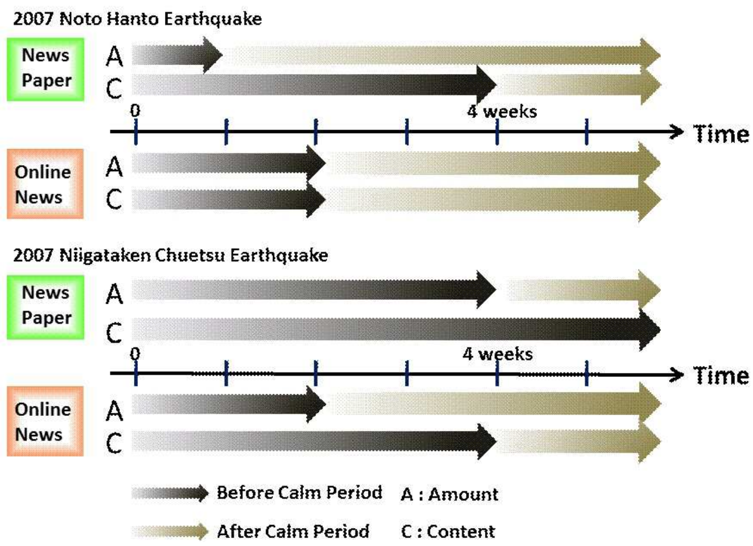

Fig. 6. Summary of media information analysis

5. Method of analysis for media information using information technology

The contents of media information have been found to be important when determining the calm period for performing the measures to counteract reputational damage. A manual analysis of media information content is not suitable for providing analysis results in real time when an earthquake occurs because the amount of information is extremely large. Therefore, an automatic method of content analysis is required. In this research, we propose an analysis method using information technologies. The details of the proposed method are described below.

5.1 Overview of proposed method

We propose a method for analyzing trends in the content of media information that compares the similarity of information over time following an earthquake. It is clear that the information about damage and human causalities is repeatedly published immediately after the earthquake and the content gradually shifts to a focus on recovery progress over time. Therefore, our method compares the content of media information immediately after the earthquake with the subsequent content of media information further from the date of the earthquake. The trends in media information are quantified by comparing the results.

An overview of proposed method is shown in Fig. 7. In the proposed method, the media information is analyzed on a daily basis. First, media information is broken down into morphemes, which are the minimum unit in language that has meaning. Association rule mining is then applied to the extracted morphemes and can extract frequently appearing words in the media information. Next, the value of χ^2 is calculated on the basis of the co-occurrence frequency of frequently appearing extracted words. By this method, important words in the media information are identified. The similarity of the content is calculated using the rank correlation coefficients of frequently appearing and important words. The trends in media information are quantified by this process.

The proposed method can schematically grasp the overall content of media information by extracting frequently appearing words based on association rule mining. In addition, the emphasis of the overall content can be obtained by extracting important words based on χ^2 value. The trend of media information can be appropriately grasped by calculating the similarity from the viewpoints of two criteria. The detail of each step is shown below.

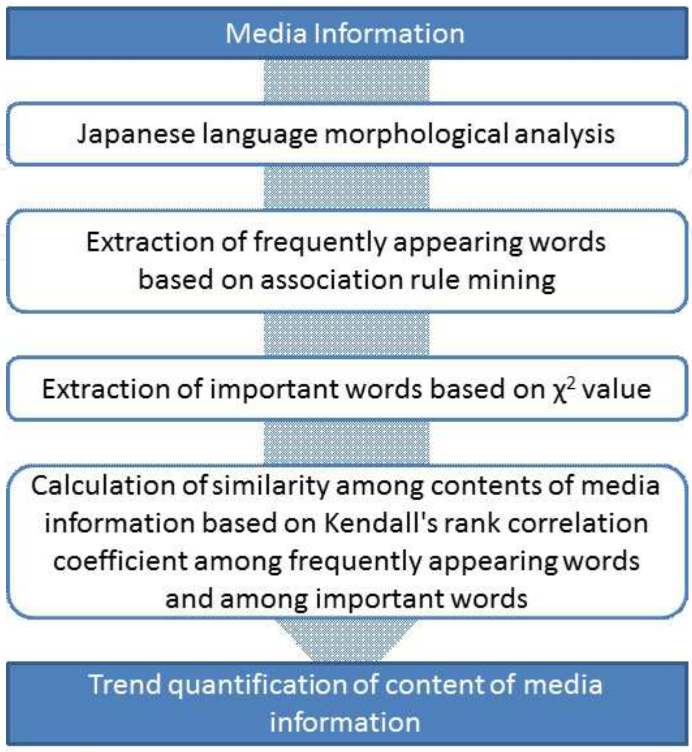

Fig. 7. Overview of proposed method of content anaylsis

5.2 Japanese language morphological analysis

In our method, we use Mecab, an open source Japanese language morphological analysis engine, in order to resolve text information into morphemes (Kudo, 2011). Only nouns are extracted from text information in this operation, and morphemes for words other than nouns (verb, adjectives, numbers, symbols, etc.) are removed.

In addition, we connect nouns extracted in the Japanese language morphological analysis that are part of multiword phrases or names. Thus, some continuous nouns are treated as one noun by connecting them. For example, the name "Sapporo city" is normally divided into two nouns—"Sapporo" and "city"— in Japanese language morphological analysis. We link both parts so that "Sapporo city" is treated as one noun. This operation can prevent an excessive resolution of one word and maintain the original meaning of the expression.

After this, a word appearance list is created, consisting of the combinations of nouns and the number of lines on which each noun is included. This operation is based on the extracted nouns and the line feed and punctuation information in the text.

5.3 Association rule mining

Basically, in our research, the content of media information is analyzed using the frequency of words, including nouns and multiword noun phrases. Namely, frequently appearing words are extracted by association rule mining in this step. We employ an Apriori algorithm, which is the association rule extraction algorithm proposed by Agawal (Honiden, 2005). In this algorithm, the user decides thresholds for support and confidence, and words having values over the thresholds are extracted.

As the first step in extracting frequently appearing words, the support value is calculated for each word in the word appearance list. The support value represents the probability of occurrence for a word. We calculate the support value by using formula (1). In formula (1), the support value considers the number of words and the number of the word types in the text is calculated, as the probability of occurrence for word is sensitive to these numbers. In the first calculation step in formula (1), X equals Y because each word consists of one noun.

$$s = P(X \cap Y) \times \frac{I \times N_{std}}{N \times I_{std}} \tag{1}$$

N : Number of words appearing in text

I : Kinds of words appearing in text

N_{std} : Criterial number of words appearing in text

I_{std} : Criterial kinds of words appearing in text

The values extracted from the media information text on the first day following the earthquake are used as the criterion of word numbers appearing and the criterion of word type appearing in the text. Next, the confidence value for each word is calculated by using formula (2). If the support and confidence values are over fixed thresholds, the word is added to the frequently appearing word list.

$$c = P(Y \mid X) \tag{2}$$

As the next step, two words in the frequently appearing word list are combined. The support and confidence values for the combined words are calculated, and the words having the values over the thresholds are also added to the frequently appearing word list. The combination of words in the frequently appearing word list is repeated until the combined words satisfying the thresholds are exhausted.

If a combined word consisting of multiple words appears only one time in the text, the combined word is not added to the frequently appearing word list. Moreover, if the support value for a word that is a subset of a combined word equals the support value for the combined word, the subset word is removed from the frequently appearing word list. These operations are performed eliminate the redundancy of words appearing in the list as single and combined words.

5.4 Calculation of the value *of* χ^2

The important words in text are often used in conjunction with some particular words. Namely, co-occurrence of words likely becomes an index representing the importance of words in the text. Thus, we analyze the co-occurrence of words in the text in order to grasp the emphasized content in the whole of the media information (Matsuo & Ishizuka, 2002).

A co-occurrence matrix is created from the words in the frequently appearing word list created by association rule mining. The expectation for the frequency of each word in the frequently appearing word list is calculated. The value of χ^2 is calculated using formula (3), based on the expectation and co-occurrence frequency of the words. If a word co-occurs with a particular word, a relationship between ancillary words likely exists among these words. Thus, a value of $\chi^{2'}$ is employed that ignores the ancillary relationship. The value of $\chi^{2'}$ is calculated by a formula (4). The important word list is created using $\chi^{2'}$ value.

$$\chi^2(i) = \sum_{w \in W} \frac{(freq(i,w) - n_i p_w)^2}{n_i p_w} \tag{3}$$

$$\chi^2(i)' = \chi^2(i) - \max_{w \in W} \left\{ \frac{(freq(i,w) - n_i p_w)^2}{n_i p_w} \right\} \tag{4}$$

$freq(i,w)$: Co-occurrence frequency of word i and w $\in$ W

n_i: Total number of co-occurrence between word i and set of frequently appearing word w

p_w: Occurrence probability of frequently appearing word

5.5 Kendall's rank correlation coefficient

Media information is collected daily. Thus, a frequently appearing word list and an important word list are created for each day. Kendall's rank correlation coefficients between the frequently appearing word lists and the important word lists are calculated using formula (5). Kendall's rank correlation coefficient for the frequently appearing word lists indicates the recapitulative similarity of media information and for the important word lists indicates the similarity of content emphasized in the media, respectively.

$$R = \frac{\sum P_{ij} - \sum Q_{ij}}{\sqrt{\frac{n(n-1)}{2} - T_x}\sqrt{\frac{n(n-1)}{2} - T_y}} \tag{5}$$

$$T_x = \sum_{i=1}^{n_x} \frac{t_i(t_i - 1)}{2} \tag{6}$$

$$T_y = \sum_{j=1}^{n_y} \frac{t_j(t_j - 1)}{2} \tag{7}$$

P_{ij}: Combination of words that have an order relation of word i > word j in list x and same order relation in list y

Q_{ij}: Combination of words that have an order relation of word i > word j in list x and an order relation of word j < word i in list y

n: Length of list

t_i: Number of words with same rank as word i in word list x

t_j: Number of words with same rank as word j in word list y

In the calculation of similarity in the media information, both of the similarities of the recapitulative content and the emphasized content can be considered by using two rank correlation coefficients between the frequently appearing word lists and the important word lists. The similarity between media information is calculated using formula (8).

$$Sim(i,j) = \sqrt{R_{freq}(i,j)^2} \times (1 + \sqrt{R_{imp}(i,j)^2} \tag{8}$$

$Sim(i,j)$: Similarity between media information of day i and media information of day j

$R_{freq}(i,j)$: Rank correlation coefficient between the frequently appearing word lists of day i and day j

$R_{imp}(i,j)$: Rank correlation coefficient between the important word lists of day i and day j

We use the absolute value of the rank correlation coefficient to calculate the similarity between media information. A negative correlation coefficient between lists means that the recapitulative contents of media information are the same and just the quantity of each topic in the media information is different. Therefore, the absolute value is used because it is clear that there is similarity between media information in this case.

The similarity between media information for a given day *i* and the previous day *i-1* is calculated by using the formula (8). In addition, the similarity between media information on a given day *i* and all previous days, (i.e., all days from day *0* to day *i-1)* is calculated and then the average value of these is calculated. The trends in media information are obtained on the basis of the time series analysis of these similarities.

5.6 Experimental method and results

In this experiment, we used the media information from web news about the Noto and Niigata Chuetsu earthquakes that were used in the previous analysis in order to confirm the validity of our proposed method. The reason why the media information from web news was employed is that it is easy to obtain the media information as digital data. The thresholds of support and confidence in the association rule mining were 0.7 and 0.015. These thresholds were determined by a heuristic method. Moreover, the top 20 words in the frequently appearing word list and the important word list were used to calculate Kendall's rank correlation coefficient.

The result of the media information analysis for each earthquake is shown in Fig. 8. In Fig. 8, if the similarity of media information between each given day and all past days and the similarity of media information between each given day and the previous day are continuously low, the mass media sent information of varying content each day that was different from past trends. Namely, a situation where the two similarity scores are continuously low indicates the turning period when the trend of media information changes.

In the results for the Noto Earthquake, the similarities to media information on all previous days and to of the immediately previous day both decreased on the 14th day after the earthquake. A decrease in similarity was also observed on 43th day after the earthquake. However, the decline on the 43th day was caused by a decrease in the amount of information. We investigated the words in the frequently appearing word lists and the important word lists in order to clarify the cause of decrease in similarity. From this investigation, we found that the words relating to earthquake damage and aftershocks were extracted until the 14th day following the earthquake and then words related to the withdrawal of self-defense forces and other events were extracted from the 14th day and beyond. Moreover, the results obtained by the proposed method corresponded with the results of content classification represented in Fig. 5.

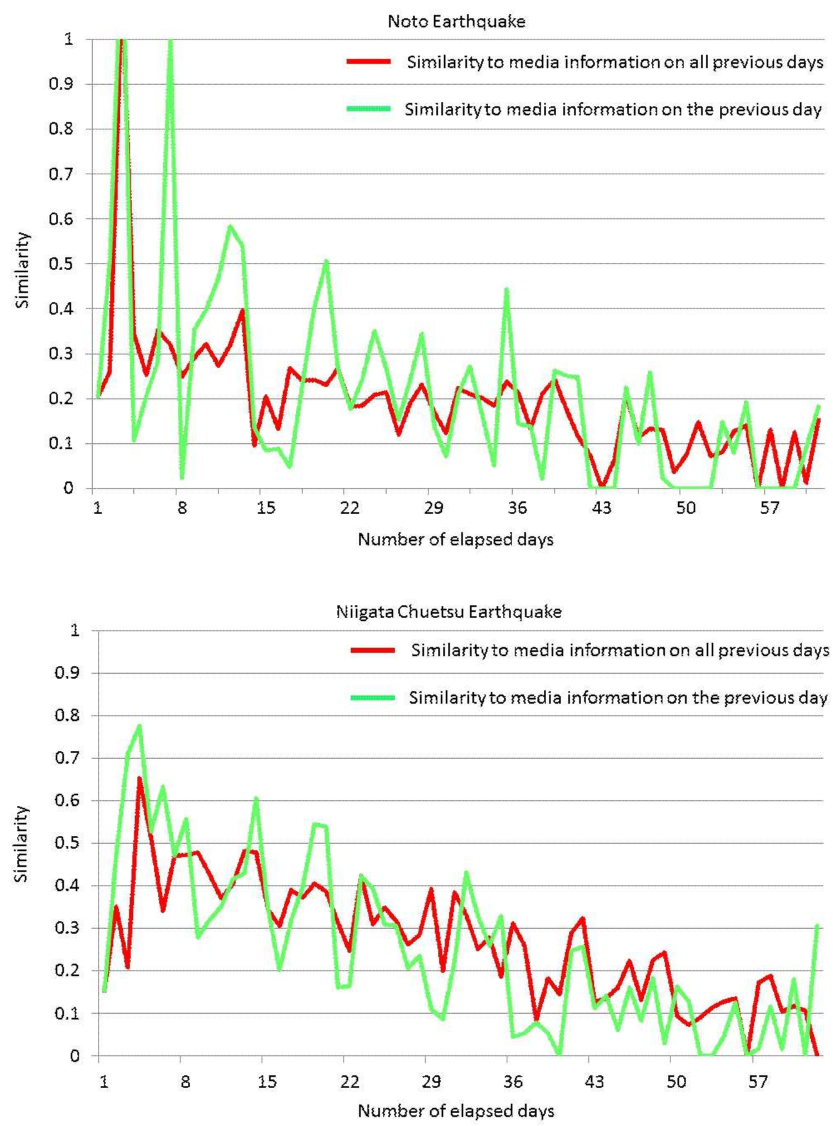

Fig. 8. Trends in media information from web news

For the Niigata Earthquake, a large decrease in similarity to the media information of the previous day was observed on the 36th day after the earthquake. The similarity to the media information of all previous days decreased on 38th day after the earthquake. We also investigated the frequently appearing word lists and the important word lists in order to strictly check the cause of the decrease. Words relating to the closure of an evacuation center were extracted on 35th day and words relating to criminal activity connected to the earthquake were mainly extracted on 36th day. It is likely that the decrease of similarity to the media information of the previous day resulted because of this difference. Moreover, the trend in words in each list changed from 37th day. However, the words extracted from media information on 37th day after earthquake partly agreed with the words extracted from media information immediately after the earthquake. For this reason, the large decrease in the similarity to the media information of all previous days was not observed on the 37th day and then emerged on the 38th day. In the results of the media content classification described in Fig. 5, the ratio of POSITIVE articles in the media started increasing from the 33rd day after the earthquake. The result obtained by the proposed method roughly agreed with the classification results of the human analysis of media information.

From these results, it was found that the change in media information could be properly obtained by the proposed method. Therefore, it is likely that effective measures to counter reputational damage could be performed based on the conditions and trends in media information by using our proposed method.

5.7 Discussion

From the experimental results described above, it was revealed that our proposed method could quantify the transition in media content and then could grasp changes in the trends in media information. In this method, media information such as damage reports was assumed to be widely disseminated immediately after the occurrence of earthquake and then that media information gradually shifts over time to other content such as recovery progress. Namely, a situation where the similarity in media information is low compared to immediately after the earthquake means that the content has shifted, which can lessen the feelings of avoidance toward neighboring tourist area near the disaster zone. However, there is the possibility that media information changes to even worse content, which would further promote the feelings of avoidance toward the neighboring tourist areas. However, it is difficult to judge using our proposed method how changes in media content affect feelings of avoidance toward neighboring tourist areas. A function must be implemented that can analyze whether the contents promote a positive or negative impression of neighboring tourist areas.

In our research, we attempted to add a function to the proposed method that can analyze the impression of media information on the public. In order to judge the impression of media information, we analyzed which frequently appearing words and important words are used in the text to get the connotation of the media information. Namely, the connotation of words was analyzed. Here, we applied dependency parsing software to sentences containing frequently appearing words and important words and then extracted the grammatical relationships. Specifically, nouns, verbs, adjectives, adverbs and conjunctions in the segments including the frequently appearing words or important words were extracted to specify how the words were used in the text. We employed CABOCHA, which is Japanese dependency structure analysis software based on support vector machines, to perform dependency parsing (Kudo & Matsumoto, 2002).

After Japanese dependency parsing, the direction of the meanings for each word was quantified by PMI-IR, which calculates the strength of emotional polar value (Tunney, 2001; Kaji & Kitsuregawa, 2007). Words representing positive things are often used together with other words that have positive meanings. In contrast, words representing negative things are often used together with other words that have negative meanings. The connotation of word was analyzed on the basis of information retrieval using a search engine in PMI-IR. Thus, we investigated whether words having positive meanings or words having negative meaning were used together frequently with the words on the frequently appearing word list and the important word list on the basis of the number of hit counts in search engine.

First, a key phrase for the search engine is created. The key phrase consists of a word from the frequently appearing word list or the important word list along with words from the list of words having a modifying relationship extracted by Japanese dependency parsing and the index of words having positive connotations. Information retrieval was conducted using a search engine. The key phrase was entered into the search engine and the number of hit counts was determined. Similarly, the number of hit counts for the key phrase was also determined with an index of words having negative connotations substituted in place of the positive word index. Moreover, the hit counts for the positive and negative index words were investigated, respectively. SO value for the key phrase was calculated by using four values as shown in formula (9).

$$SO(ph) = \log_2 \left(\frac{hits("Ph"Near"GW") \times hits("BW")}{hits("Ph"Near"BW") \times hits("GW")} \right) \tag{9}$$

In the formula (9), *ph* represents a key phrase consisting of a word in the frequently appearing word list or the important word list and the words having a modifying relationship. Further, *hits("Ph" Near "GW" or "BW")* indicates the hit count from information retrieval using the key phrase, the index word and the NEAR operator. Multiple SO values were calculated for each word in the frequently appearing word list and the important word list because they were present in multiple sentences along with different modifying words. The average SO value is used each word. In addition, the impression level of media information was calculated using formula (10). The impression level of media information is calculated using multiple SO values because the frequently appearing word list and the important word list contain multiple words.

$$IMG = \sum_{j=1}^{n} \left(SO\_F_j \times \frac{freq_j}{\sum_{p=1}^{n} freq_p} \right) \times \sum_{k=1}^{m} \left(SO\_I_k \times \frac{imp_k}{\sum_{q=1}^{m} imp_q} \right) \tag{10}$$

SO_F_j : SO value for the jth word in the frequently appearing word list

SO_I_k : SO value for the kth word in the important word list

$freq_j$: Support value for the jth word in the frequently appearing word list

imp_k : Importance value for the kth word in the important word list

$\sum_{p=1}^{n} freq_p$: Sum of support values for all frequently appearing words in word list

$\sum_{q=1}^{m} \mathrm{imp}_q$: Sum of important values for all important words in word list

m, n : Length of list

We applied the impression analysis to the media information from web news for the Niigata Chuetsu Earthquake. We used Google as the search engine for the impression analysis. Combinations of words having positive or negative connotations were used as index words, such as words that could be considered "good" and "bad" and having to do with "relief" and "fear". The impression values (IMG) were calculated for these combinations, and then the average value was used as the impression level for media information.

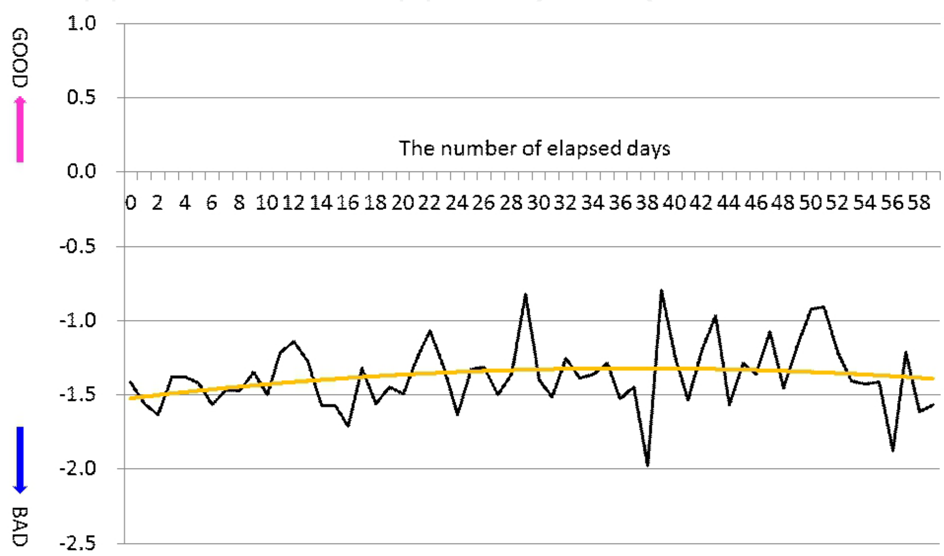

Fig. 9. Results of impression analysis of media information

Figure 9 shows the results of the impression analysis. From the experimental result, it was revealed that the impression level of media information had negative values on each day following the earthquake. Immediately after an earthquake, the media information gives a negative impression to people. Therefore, the values for all days are likely to be negative. However, a pattern approximating a curve can be seen in Fig. 9, as a slightly positive increase in the impression level was observed. Namely, the impression level from media information is assumed to indicate a gradual recovery trend. However, these results using the search engine did not completely correspond to the analysis results from media information categorized by humans. In this experiment, as described above we employed two combinations of words, positive and negative, as index words (i.e., "good" and "bad", "relief" and "fear"). It is likely that the appropriate index word for each frequently appearing word and important word are different because the media can use words in various contexts in media information. Therefore, improvement is needed in the impression analysis function to be able to dynamically change index words depending on the word used when investigating the impression. Improving the impression analysis function will be one of our goals in future work.

6. Conclusion

In this chapter, we discussed the causes of reputational damage in neighboring tourist areas near earthquake disaster zones. In addition, we analyzed the conditions and trends in media information in actual situations where tourism areas incurred reputational damage during earthquake disasters.

The analysis found that the amount of media information was highest immediately after the occurrence of earthquake and that the amount of media information gradually decreased over time, depending on the nature of the damage and the scale of earthquake. Moreover, in terms of the content of media information, negative information promotes feelings of avoidance in the public towards visiting neighboring tourist areas for sightseeing was sent immediately after the earthquake. Over time, the media content gradually shifted towards positive information, which eases the feelings of avoidance. The analysis of media information in newspapers showed that the turning point in media information from negative to positive was 4 weeks from the date of the earthquake in early cases, from which point the amount of media information and its content is suitable for starting measures to counteract reputational damage in surrounding areas. In late cases, the turning point was 6 weeks after the earthquake. On the other hand, the analysis results of web news revealed that turning point in media information was as soon as 2 weeks in early cases and 4 weeks in late cases.

The analysis indicated that content analysis of media information was more important when considering when to begin measures to counter reputational damage. However, content analysis has higher cost in comparison with the analysis of amount of media information. Content analysis is difficult to perform manually because the amount of media information is large and analysis must be performed rapidly in order to be effective when planning measures to reduce reputational damage. We proposed an analysis method to realize an automated content analysis of media information. In the proposed method, media information was analyzed on the basis of its characteristics following an earthquake. Media information that has a negative impact on neighboring tourist areas is immediately sent to the public after an earthquake and the content of media information gradually becomes more positive over time. In the analysis, media information was analyzed by comparing the similarity to media information immediately after earthquake.

Moreover, we used the proposed method to analyze media information on the 2007 Niigata Chuetsu Earthquake and the 2007 Noto Earthquake in order to confirm the adequacy of the proposed method. From the experimental results, it was revealed that the similarity between media information immediately after an earthquake was high and that the similarity was then reduced gradually over time. This change indicates that the proposed method could grasp how media information changed over time and how media content promoted or eased feelings of avoidance toward neighboring tourist resorts. Therefore, measures to counter reputational damage could be developed based on the conditions and trends in media information using the proposed method.

However, it was difficult to judge the effect of media content on causing and easing feelings of avoidance in the public. Therefore, we discussed a function that analyzes the impression of media information using Japanese dependency parsing and PMI-IR. From the experimental results, the impression of media information was found to become gradually more positive, although the function's results were different from the results of media information classified by a human. The reason for this difference was likely the lack of flexibility in the selection of index words used to investigate the polar direction of the meaning of a word. Our future work will be to implement dynamic index word selection that is capable of rating each analyzed word appropriately.

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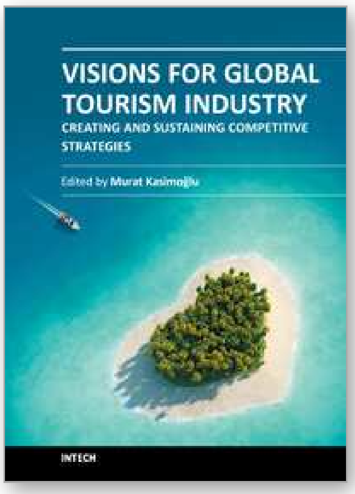

Visions for Global Tourism Industry - Creating and Sustaining Competitive Strategies

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We have been witnessing huge competition among the organisations in the business world. Companies, NGO's and governments are looking for innovative ways to compete in the global tourism market. In the classical literature of business the main purpose is to make a profit. However, if purpose only focus on the profit it will not to be easy for them to achieve. Nowadays, it is more important for organisations to discover how to create a strong strategy in order to be more competitive in the marketplace. Increasingly, organisations have been using innovative approaches to strengthen their position. Innovative working enables organisations to make their position much more competitive and being much more value-orientated in the global tourism industry. In this book, we are pleased to present many papers from all over the world that discuss the impact of tourism business strategies from innovative perspectives. This book also will help practitioners and academician to extend their vision in the light of scientific approaches.

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