NETWORK FAILURE DETECTION SYSTEM FOR TRAFFIC CONTROL USING SOCIAL INFORMATION IN LARGE-SCALE DISASTERS

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ABSTRACT

When the Great East Japan Earthquake occurred in 2011, it was difficult to grasp all network conditions immediately using only information from sensors because the damage was considerably heavy and the severe congestion control state occurred. Moreover, at the time of the earthquake, telephone and Internet could not be used in many cases, although Twitter was still available. In an emergency such as an earthquake, users take an interest in the network condition and provide information on networks proactively through social media. Therefore, the collective intelligence of Twitter is suitable as a means of information detection complementary to conventional observation. In this paper, we propose a network failure detection system that detects candidates of failures of telephony infrastructure by utilizing the collective intelligence of social networking services. By using this system, more information, which is useful for traffic control, can be detected.

Keywords— Twitter, social information, failures of telephony infrastructure, traffic control

1. INTRODUCTION

Large-scale disasters such as earthquakes often cause network failures because base stations and network facilities are damaged and many users are trying to access the network at the same time. In cases of emergency, it is important that telephone and Internet be available. Therefore, the necessity for failure detection in large-scale disasters is high. Usually, network conditions are monitored by sensors. However, when the Great East Japan Earthquake occurred in 2011, it was difficult to grasp all network conditions immediately using only information from sensors because the damage was considerably heavy and the severe congestion control state occurred. [1].

In subsequent research on the Great East Japan Earthquake [2], survey participants responded that they were able to use Twitter [3]. Twitter is also advantageous in that it can obtain information from users in real time. In an emergency such as an earthquake, users take an interest in the network condition and provide information on networks proactively through social media. Hence, Twitter can be used to obtain information on the locations and causes of network failures and on the degree of impact to users, which cannot be obtained using only sensors. Therefore, the collective intelligence of Twitter is suitable as a means of information detection complementary to conventional observation. Against this background, we propose a network failure detection system that detects candidates of failures of telephony infrastructure by utilizing the collective intelligence of social networking services. This system is targeted to network managers, who wish to detect failures of telephony infrastructure automatically in case of emergency.

Here, there is an issue if Twitter will be accessible when Internet services are down. However, if a wireless LAN access is not available, other services such as 3G network and LTE may be able to be used. Moreover, people in areas where failures don't occur provide information on the failures of telephony infrastructure.

Among the earthquakes that occurred in 2014, we detected failures of telephony infrastructure with a high degree of accuracy [4]. However, in the case of large-scale earthquakes such as the Great East Japan Earthquake, more information, which is useful for traffic control, is needed. For example, when our system detects telephone trouble, we want to classify whether users cannot get through *to* the detected location or cannot get through *from* the detected location. In this case, the areas where a failure is likely to occur should be the former. Therefore, in this work, we investigated tweets sent out during the Great East Japan Earthquake and used our findings to develop a method that uses machine learning to classify the detected locations into two groups.

The remainder of this paper is organized as follows. Section 2 introduces related research studies and Section 3 gives an overview of our proposed system. Sections 4 and 5 respectively discuss the candidate data detection method and the location classification method that are a part of our proposed system. In Section 6, we describe a visualization of the results of the location classification method and the external information. We conclude in Section 7 with a brief summary and a mention of the future direction of our research.

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2. RELATED WORK

There are currently a number of methods that detect events occurring in the real world (earthquakes, landslides, fire, etc.) by analyzing the data in social media [5][6][7][8][9]. Sakaki et al. [5] introduced a method to detect earthquakes early and estimate their locations by considering each Twitter user as a sensor. The Ministry of Land, Infrastructure, Transport and Tourism [6] introduced a method to detect the signs and occurrences of landslides early on the basis of the tweets of residents of the areas where a disaster is likely to occur. Our current work differs from these existing methods in that 1) the existing methods restrict their focus to the occurrence of an event and do not detect more detailed information when large events occur, and 2) they do not utilize the external information issued by public agencies, which would be useful in terms of increasing the accuracy.

Our method is unique in that it 1) increases the accuracy of network failure detection using collective intelligence by filtering out irrelevant tweets, and 2) detects information for traffic control. Moreover, we use social networking services for network management. Tongqing et al. [10] reported that users posted messages on Twitter before they called a customer service center if they experienced network failures, and Takeshita et al. [11][12] had a similar motivation to our own in that they use tweets related to network performance issues in order to oversee network operation. However, our present work differs from these in that 1) we focus on natural disasters and 2) we detect failures of telephony infrastructure using more that just tweets.

3. OVERVIEW OF PROPOSED METHOD

An overview of our proposed network failure detection system is given in Figure 1. Figure 2 gives an overview of the candidate data detection method that is a part of the proposed system.

The process flow of the proposed method is as follows.

(1) Set specific keywords that can detect failures of telephony infrastructure and collect tweets containing the keyword.
(2) Classify the tweets in accordance with location information into each location group.
(3) Collect tweets without location information but specifying the same failure to increase the amount of candidate data. We calculate characteristic words with the data set of (2) and add tweets containing the words into the data set of (2).
(4) Consider post time of each tweet and apply temporal filtering to cut irrelevant tweets.
(5) Classify location from tweets detected by our system as to whether the failure happened at this or another location.
(6) Obtain external information such as Earthquake Early Warning and match this with the failure information detected by (5).
(7) Visualize failure information on Google Maps.

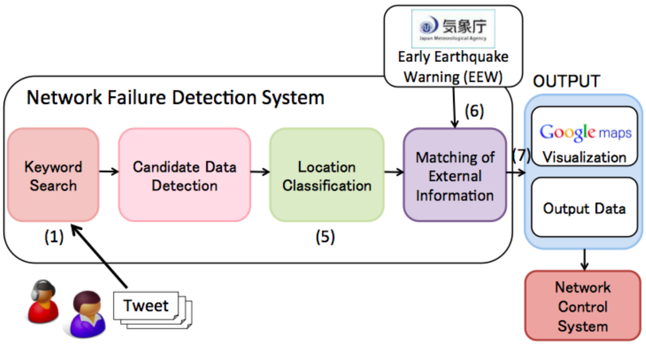


Figure 1. Network failures detection system.

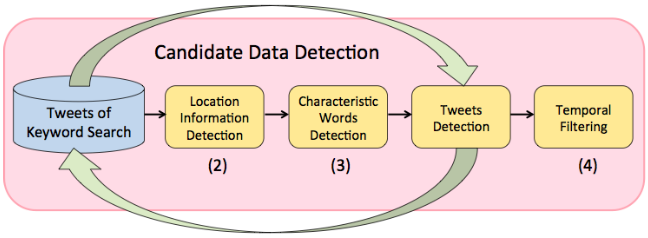


Figure 2. Candidate data detection.

It is important that failures of telephony infrastructure be detected immediately. For real-time processing, we collect tweets every minute and use tweets in the last 60 minutes as potential tweets for failure detection. This system then outputs failure information for each detected location.

4. CANDIDATE DATA DETECTION METHOD USING SOCIAL NETWORKING SERVICES

4.1. Keyword Search

We set specific keywords that represent telephone trouble using a Search API supported by Twitter Inc. to collect tweets about failures of telephony infrastructure. The keywords are phrases that mean users cannot get through by telephone in Japanese.

4.2. Location Information Detection

Various tweets can be associated with location. For example, Twitter users may register their location on their profile, and sometimes they attach Geotagging to a tweet. We conducted a morphological analysis of tweets and their registered Geotagging locations by using MeCab [14], which separates sentences into a set of words. Latitude and longitude details of the Geotagging are converted into a city name using the Yahoo! reverseGeoCoder API [15] supported by Yahoo! Inc. We counted the number of occurrences of location names and detected them that appeared more than a certain number of times. In this work, we define the threshold of occurrences as five times. Then, we classified the tweets of Section 4.1 in accordance with the detected location information into each location group.

4.3. Characteristic Words Detection

To collect tweets that do not contain the same location but refer to the same failure, we detect characteristic words in the tweets. We then collect tweets that contain the detected characteristic words and not the other location information and add them to the tweets for each piece of location information.

”Characteristic words” are found in tweets for each piece of location information by detecting only nouns using MeCab. We exclude byte symbols and half-width letters and numbers. Then, we calculate a TFIDF (Term Frecuency Inversed Document Frequency) value for each detected noun and define a noun that has a TFIDF value greater than or equal to 0.2 as a characteristic word.

TFIDF is a numerical statistic that is reflected how important a word is to a document. TF value is the term frequency. Therefore, words that appear many times are important. IDF value is the inverse document frequency. The smaller it is, the greater the number of tweets that a word appears is. Therefore, it has a role to increase the importance of words that only appear in specific tweets. TFIDF value is calculated by multiplicating a TF value and a IDF value.

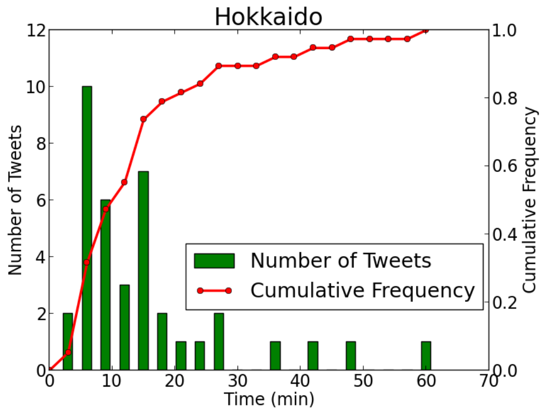
In this study, TFIDF value is calculated as follows; where the number of detected nouns is N, experimental tweets that are classified into each location group of Section 4.2 are TW_e, and the roughly 100,000 tweets obtained using Twitter Inc.’s Streaming API [16] are TW_{10}. These TW_{10} are tweets of normal period that are not be set any keywords, and they are utilized to calculate IDF value. By introducing TW_{10}, N can be compared with words of normal period.

$$TF\text{value} = \frac{\text{the number of times } N \text{ appears in } TW_e}{\text{the total number of words that appear in } TW_e} \quad (1)$$

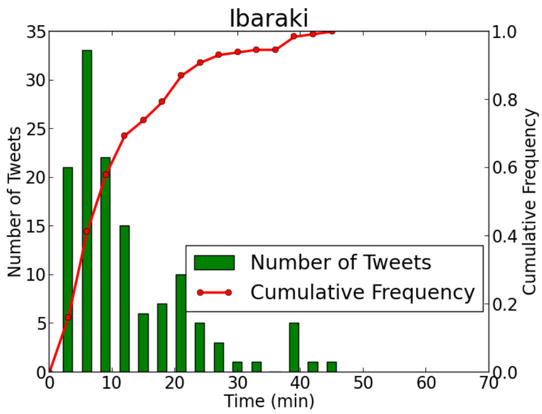
$$IDF\text{value} = \frac{\text{the total number of tweets of } TW_e \text{ and } TW_{10}}{\text{the number of tweets that contain } N \text{ in } TW_e \text{ and } TW_{10}} \quad (2)$$

4.4. Temporal Filtering

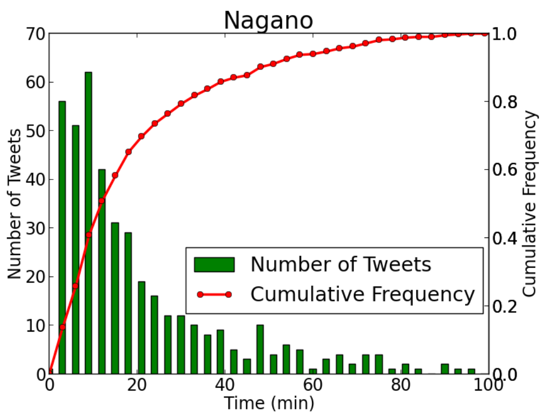
In each piece of location information, there are a number of tweets that are unrelated to failures of telephony infrastructure. Therefore, we consider the timestamps of tweets and discard any tweets that are unrelated. Twitter users tend to simultaneously post similar tweets when large-scale disasters happen, and in this study, we consider this feature and determine a certain threshold of time to eliminate tweets. To determine this threshold, we examine the time variations of the number of tweets that refer to failures of telephony infrastructure and generalize them.



(a) Earthquake in Hokkaido



(b) Earthquake in Ibaraki



(c) Earthquake in Nagano

Figure 3. Time variations of tweets that refer to failures of telephony infrastructure.

Figure 3 shows each time variation of the number of tweets that refer to failures of telephony infrastructure in the case of an earthquake in Hokkaido on July 8, 2014, an earthquake in Ibaraki on September 16, 2014, and an earthquake in Nagano on November 22, 2014 (green bar graph).

As shown in Figure 3, the number of tweets increased rapidly after earthquakes occurred and then eventually saturated.

This result shows that time variations of the number of tweets in earthquakes are characteristic. In this study, we consider cumulative frequency since the number of samples is small. Figure 3 shows the actual data of cumulative frequencies (red line). The time variations of cumulative frequencies are similar to the cumulative distribution function of an exponential distribution. Hence, we fitted each time variation of a cumulative frequency to the cumulative distribution function of exponential distributions. This cumulative distribution function is defined as

$$f(x) = 1 - e^{-\lambda x} \tag{3}$$

Figure 4 shows the results of fitting earthquakes in Hokkaido, Ibaraki, and Nagano.

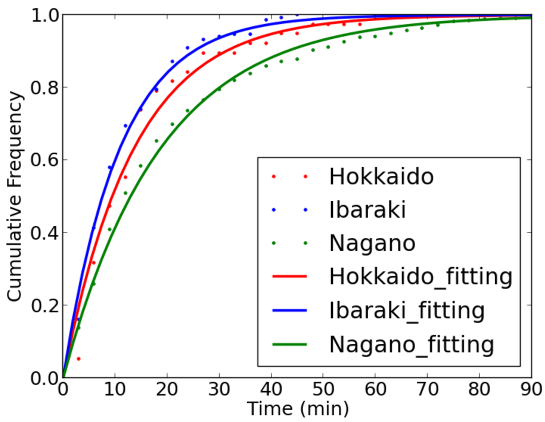


Figure 4. Results of fitting cumulative distribution functions of an exponential distribution.

Results showed that all time variations of cumulative frequencies were fitted to the cumulative distribution functions of an exponential distribution. This indicates that the time variations of the number of tweets can be approximated to an exponential distribution. Moreover, since this is an exponential distribution, we can capture 80% of the events in 60 minutes. Hence, for real-time processing, we collect tweets every minute and use tweets in the last 60 minutes as potential tweets for failure detection.

5. LOCATION CLASSIFICATION METHOD USING MACHINE LEARNING

Among the earthquakes that occurred in 2014, the candidate data detection method (Section 4) was able to detect failures of telephony infrastructure with a high degree of accuracy [4]. However, in the case of large-scale earthquakes such as the Great East Japan Earthquake, more information, which is useful for traffic control, is needed. For example, when our system detects telephone trouble, we want to classify whether users cannot get through *to* the detected location or cannot get through *from* the detected location. In this case, the areas where a failure is likely to occur should be the former. Therefore, on the basis of our analysis of tweets sent out during the Great East Japan Earthquake, we developed a method that utilizes machine learning to classify the detected locations into two groups. Table 1 shows examples of tweets that were detected with the candidate data detection method.

Table 1. Examples of tweets of candidate data detection method.

A.	「宮城へ電話繋がらないよ... 心配だ」 (I cannot get through to Miyagi...I'm worried.)
B.	「渋谷なう 電話繋がらない」 (I'm in Shibuya now. I cannot get through.)

Here, tweetA shows that the user cannot get through *to* the detected location (Miyagi) while tweetB shows that the user cannot get through *from* the detected location (Shibuya). Therefore, tweetA and tweetB are different kinds of tweets. Classifying tweets in this way enables us to obtain more information, which is useful for traffic control. Hence, we classify tweets detected with the candidate data detection method. The detected tweets can be classified into the following three types:

(1) tweets that mean users cannot get through *to* the detected location (= Data Set A)
(2) tweets that mean users cannot get through *from* the detected location
(3) undeterminable tweets

There is a possibility that tweets from the location of the failure are classified as (1). Therefore, we focus on Data Set A of (1). In this paper, we classify the tweets into tweets that mean either users cannot get through to the detected location of (1) or other tweets, which include both (2) and (3). We propose tweet detection with a rule-based approach and tweet classification using machine learning.

5.1. Tweet Detection by the Rule-Based Approach

Figure 5 shows the flow of tweet detection with the rule-based approach.

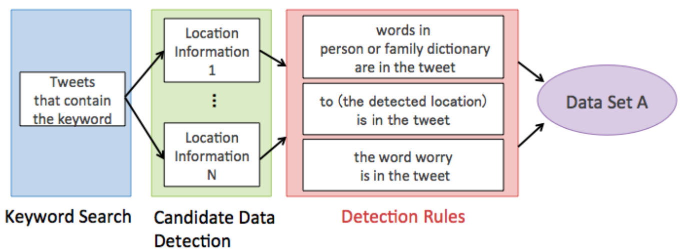


Figure 5. Flow of tweet detection with rule-based approach.

First, we perform the candidate data detection method and collect the tweets that are obtained by the keyword search for each item of location information. Next, for each detected location, we judge whether the tweets satisfy the extraction rules. We extracted the patterns common to Data Set A and then made rules to classify the tweets. The extraction rules are:

(1) words in person or family dictionary are in the tweet
(2) *to (the detected location)* is in the tweet
(3) the word *worry* is in the tweet

The person or family dictionary is a dictionary that includes words related to people, e.g., mother, son, and sister. In this work, we selected these rules because an evaluated value was the best among other rules. Table 2 shows examples of tweets that satisfy these rules.

Table 2. Examples of tweets that satisfy these rules.

(1)	「岩手の**母**に電話がつながらない」 (I cannot get through to my *mother* in Iwate.)
(2)	「**仙台に**電話つながらないよ」 (I cannot get through *to Sendai*.)
(3)	「宮城のほうはかなり揺れてたみたいです。 今は電話しても繋がらないので、**心配**です。」 (Miyagi seems to have shaken quite a lot. I cannot get through now, so I'm *worried*.)

If a tweet satisfies any one of these rules, the tweet is classified as Data Set A.

5.2. Location Classification with the Machine Learning

In order to classify whether the detected tweets are Data Set A or other tweets, we created a classifier using a support vector machine (SVM). SVM-light was used as a classifier. In the classification with machine learning, we use only Bag of Words (BoW) and the rules of the tweet detection with the rule-based approach as features. When rules are added as features, the subjects of BoW are nouns, verbs, and adjectives.

5.3. Evaluation

Table 3 lists the results of tweet detection with the rule-based approach and the location detection with machine learning. Tweets in the Great East Japan Earthquake that were detected with the candidate data detection method were used as evaluation data. These data are made up of 726 tweets that mean users cannot get through to the location and 300 other tweets. We use leave-one-out cross validation as an assay method of the classification with machine learning.

Adding the rules of the rule-based approach as features can increase F-value, which demonstrates that adding rules is effective. Furthermore, when rules were added in the classification of the machine learning, F-value increased by about 10 points in comparison to tweet detection with the rule-based approach.

Table 3. Evaluation of data classification.

Method	Precision	Recall	F-value
Detection with rule-based approach	0.8170	0.8058	0.8114
Classification with machine learning (only BoW)	0.8166	0.9752	0.8889
Classification with machine learning (with rules)	0.8606	0.9862	0.9191

6. VISUALIZATION OUTPUT OF DETECTED FAILURE

We match the disaster information issued by public agencies in order to determine the cause and the location of failures that were detected using our proposed method. External information such as Earthquake Early Warning (EEW) issued via Twitter was used here.

In this study, we obtain EEW through tweets, which broadcast EEW contents indirectly. We then analyze the warnings and obtain the time, position, and strength of the earthquake.

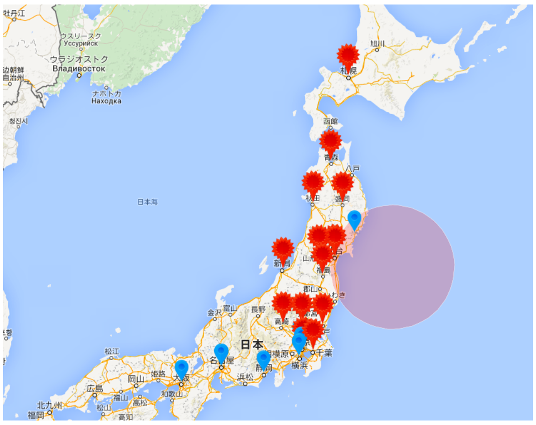
We take the results detected with the candidate data detection method and location classification method using the data of Section 5, match them with the external information, and then visualize them on Google Maps. We visualize the correct classification results manually to obtain the correct data on the location classification method. Therefore, we can confirm the effectiveness of the proposed method. Figure 6(a) shows the results using the proposed method and Figure 6(b) shows the manual classification results.

Colored pins represent the situation in the area where the pin is stuck, with red indicating that users cannot get through to the area and blue indicating the other situation (users cannot get through from the area, etc.). Seismic intensity obtained by EEW is set to the center of a circle, with the radius of the circle dependent on the magnitude of the quake. In Figure 6(a), the red pins are close to the circle, indicating that a major failure occurred near the seismic intensity. The blue pins are located further away from the seismic center, indicating that a failure had not occurred in this area but that users could not get through to people near the seismic center.

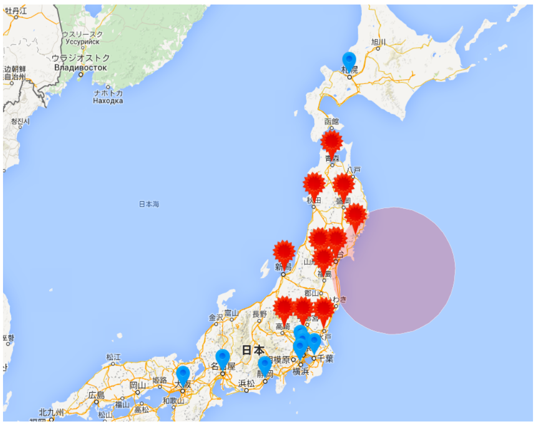
When we compared the results in Figures 6(a) and 6(b), no difference could be seen. This demonstrates that our proposed method performs well.

7. CONCLUSION

When the Great East Japan Earthquake occurred in 2011, it was difficult to quickly grasp all network conditions because the amount of information on the damage and the congestion control state, which is needed to understand the damage, was enormous. Moreover, at the time of the quake, telephone and Internet could not be used, although Twitter was still available. In an emergency such as an earthquake, users take an interest in the network condition and provide information on networks proactively. In this paper, we proposed a network



(a) Results using proposed method



(b) Results classified manually

Figure 6. Visualization results of Great East Japan Earthquake.

failure detection system that detects candidates of failures of telephony infrastructure by utilizing the collective intelligence of social networking services.

Among the earthquakes that occurred in 2014, we detected failures of telephony infrastructure with a high degree of accuracy. However, in the case of large-scale earthquakes such as the Great East Japan Earthquake, more information, which is useful for traffic control, is needed. Therefore, we proposed a method that uses machine learning to classify locations that had been detected with the candidate data detection method into two groups. By visualizing tweets sent out during the Great East Japan Earthquake, along with information obtained by EEW on Google Maps, we showed that the location classification method using machine learning works effectively.

In this work, network failure information was detected using our system. As the next step, we plan to use the detected information to construct a system that can control the network.

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