Development of Failure Detection System for Network Control using Collective Intelligence of Social Networking Service in Large-Scale Disasters

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ABSTRACT

When the Great East Japan Earthquake occurred in 2011, it was difficult to immediately grasp all telecommunications network conditions using only information from network monitoring devices because the damage was considerably heavy and a severe congestion control state occurred. Moreover, at the time of the earthquake, telephone and e-mail services could not be used in many cases, although social networking services (SNSs) were still available. In an emergency, such as an earthquake, users proactively convey information on telecommunications network conditions through SNSs. Therefore, the collective intelligence of SNSs is suitable as a means of information detection complementary to conventional observation through network monitoring devices. In this paper, we propose a network failure detection system that detects telephony failures with a high degree of accuracy by using the collective intelligence of Twitter, one of the most widely used SNSs. We also show that network control can be performed automatically and autonomically using information on telecommunications network conditions detected with our system.

Keywords

Twitter, SNSs, Collective Intelligence, Failure Detection, Telephony Failures, Network Control, DPN

1. INTRODUCTION

Large-scale disasters, such as earthquakes, often cause telephony failures because base stations and network facilities become damaged and many users try to access the telecommunications network at the same time. In such emergencies, it is important that communications via telephone and e-mail services be available. Usually, network conditions can only be grasped using network monitoring devices. However, when the Great East Japan Earthquake [1] occurred in 2011, it was difficult to immediately grasp all telecommunications network conditions using only information from network monitoring devices because the damage was considerably heavy and a severe congestion control state occurred [2].

Conventionally, telecommunications network conditions are monitored using information from inside a network, using only network monitoring devices [3]. To solve the abovementioned problem, we propose a network failure detection system using information from outside a network that is complementary to network monitoring devices.

In subsequent research on the Great East Japan Earthquake [4], survey participants responded that they were able to use social networking services (SNSs). Such services are also advantageous in that they can obtain information from users in real time. In an emergency, such as an earthquake, users proactively convey information about telecommunications network conditions through SNSs. For example, Twitter can be used to obtain information on the locations and causes of telephony failures and on the degree of impact to users, which cannot be obtained using only network monitoring devices. Therefore, the collective intelligence of SNSs is suitable as a means of information detection complementary to conventional observation using network monitoring devices. The objective of this study was to achieve automatic and autonomic network control by using collective intelligence analyzed from Twitter [5], one of the most widely used SNSs. This system is targeted to network managers who need to automatically detect telephony failures during emergencies.

Twitter accessibility is an issue when Internet services are down. However, if wireless LAN access is not available, other services such as 3G networks and LTE networks may be used. Moreover, people in areas where failures have not occurred can provide information on telephony failures.

The contributions of this work are summarized as follows.

1. By designing and prototyping an SNS-based network failure detection system, we can detect telephony failures with a high degree of accuracy and prioritize locations for network recovery.

HT '16, July 10-13, 2016, Halifax, NS, Canada

DOI: http://dx.doi.org/10.1145/2914586.2914620

2. By integrating our SNS-based network failure detection system into a network control system, we can automatically and autonomically perform network control using the collective intelligence of SNSs.

The remainder of this paper is organized as follows. In Section 2, we introduce related research studies and give an overview of our proposed system in Section 3. In Section 4, we discuss the determination of initial keywords and a candidate data detection method. In Section 5, we discuss the location classification method and degree of significance calculation in Section 6. In Section 7, we give an overview of our network control system using information detected with our network failure detection system. We conclude the paper in Section 8 with a brief summary and discuss future research directions.

2. RELATED WORK

There are a number of methods for detecting detailed information by analyzing the data from SNSs when large events occur [6–18]. Mizuno et al. [18] introduced a system to detect disaster situations using the content of tweets and location information posted by users during a disaster. This study is similar to ours in that it was focused on detecting not only the occurrence of an event but also secondary damage caused by it for managers. However, our study differs from these previous ones because we particularly focused on the detection of network failures and automatic network control using detected information.

Conventionally, network control is performed using information detected using network monitoring devices [3]. The ITU-T Focus Group on Disaster Relief Systems [3] detects network failures with a monitoring system using a wireless sensor network in emergencies and automatically notifies network managers when an event level exceeds the warning level. On the other hand, our study is unique in that we focused on performing network control using the collective intelligence of SNSs. Our study complements the fact that it is difficult to grasp network conditions for users by correctly using conventional methods. Qiu et al. [19] reported that users posted messages on Twitter before they called a customer service center if they experienced network failures. This shows that using Twitter is effective in detecting network failures. Takeshita et al. [20–22] had a similar motivation to ours in that they used tweets related to network performance issues to oversee network operation. Our study differs from these previous ones in that they only performed failure detection during normal periods. We focused on natural disasters and the results from a system that performs network control on the basis of detected information.

3. OVERVIEW OF PROPOSED SYSTEM

An overview of our proposed network failure detection system is given in Figure 1.

The process flow of the proposed system is as follows.

(1) Determine initial keywords about telephone failures by detecting failure expressions using a bootstrap method and collect tweets containing the keywords.
(2) Classify the tweets of (1) in accordance with location information into each location group.
(3) Calculate characteristic words with the data set of (2) and add tweets containing the words to the data set of (2).

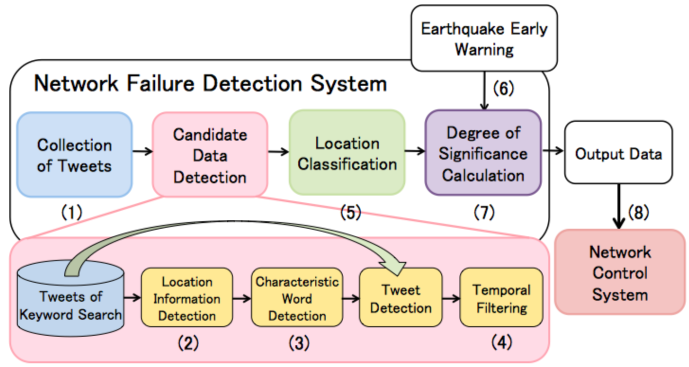

Figure 1: Network failures detection system

(4) Consider the post time of each tweet and apply temporal filtering to cut irrelevant tweets.
(5) Classify location from tweets detected using the candidate data detection method as to whether the failure occurred at this or another location.
(6) Analyze external information, such as earthquake early warning, and obtain the time, position, and strength of the earthquake.
(7) Calculate the degree of significance for network recovery.
(8) Perform network control automatically and autonomically using information on telecommunications network conditions detected with our system.

It is important that telephony failures 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. The proposed system outputs failure information for each detected location and updates the analysis results within one minute.

With this system, detailed information about the situation of a telecommunications network for users can be acquired. It is then possible to control traffic on the basis of contents in accordance with the information.

4. DETAILS OF DATA DETECTION METHOD OF PROPOSED SYSTEM

In this chapter, we discuss the determination of initial keywords and the candidate data detection method of our proposed system. Then, we discuss an evaluation experiment.

We used the corpus of tweets in Japanese from the Great East Japan Earthquake because our system is targeted for large-scale disasters. Table 1 lists the details of the corpus. This corpus includes various types of tweets in addition to those about telephony failures.

Table 1: Corpus of tweets from Great East Japan Earthquake

Date	2011/03/11
Number of Tweets	8,815,519

4.1 Determination of Initial Keywords

To determine the initial keywords that are set in the keyword search of our system, we perform the detection of failure expressions using a bootstrap method [23]. Figure 2 shows the flow of the detection of failure expressions using a bootstrap method.

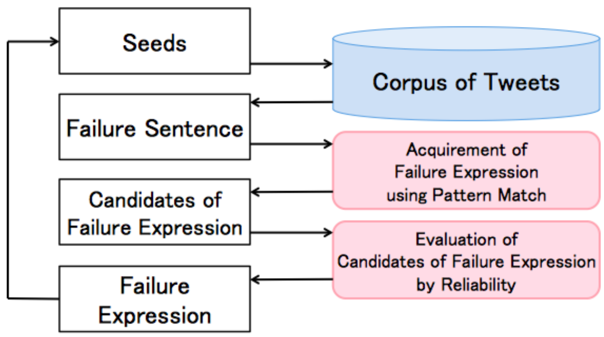

Figure 2: Detection of Failure Expression using a bootstrap method

First, we give initial seeds to the corpus of tweets from the Great East Japan Earthquake and collect tweets containing the seeds. All the tweets of the corpus contain the word "telephone". We then define the detected tweets as failure sentences. In this study, the words "congestion", "wrong", and "out of order" in Japanese were set to the initial seeds to obtain tweets about telephone problems. Next, we acquired the failure expression candidates using pattern match. This means that the combinations of verbal imperfective forms and negative auxiliary verbs are acquired from the failure sentences using the pattern match of a part of speech. Next, we score the reliability of detected failure expression candidates, because once low-precision results are obtained, the rate will continue to fall. The reliability of failure expression candidates is calculated as follows. When the set of failure sentences that contain a *candidate* that is a failure expression is S, the distance between the word "telephone" and the *candidate* in a sentence is $distance(s)$.

$$score(candidate) = \sum_{s \in S} \frac{1}{distance(s)} \quad (1)$$

This formula is based on the assumption that a word that appears many times in failure sentences and emerges close to the word "telephone" is likely to have a relation to failures. Then, the top N% of *candidate* is defined as failure expressions. These expressions are given to the corpus as new seeds, and the same procedure is repeated. The failure expressions obtained by repeating this procedure a certain number of times are defined as initial keywords for our system.

4.2 Candidate Data Detection Method

In this section, we give an overview of the candidate data detection method of our system.

4.2.1 Keyword Search

We set the obtained initial keywords using a Search API [24] to collect tweets regarding telephony failures.

4.2.2 Location Information Detection

Various tweets can be associated with location. For example, Twitter users may register their location on their profile, and sometimes they geotag a tweet. We conducted a morphological analysis of tweets and their registered geotagged locations by using MeCab [25], which separates sentences into a set of words. Latitude and longitude details of geotags were converted into city names using the Yahoo! reverseGeoCoder API [26]. We then classified the tweets of the keyword search in accordance with the detected location information into each location group.

4.2.3 Characteristic Words Detection

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

4.2.4 Temporal Filtering

In each piece of location information, there are a number of tweets that were unrelated to telephony failures. Therefore, we considered the timestamps of tweets and discarded tweets that were unrelated. Twitter users tend to simultaneously post similar tweets when large-scale disasters occur, and in this study, we considered this feature and determined a certain time threshold to eliminate tweets. To determine this threshold, we examined the time variations of the number of tweets that referred to telephony failures and generalized them. Figure 3 shows the time variation of the number of tweets that referred to telephony failures during an earthquake in Nagano on November 22, 2014. The green bars show the number of tweets and the red line shows the cumulative frequency value.

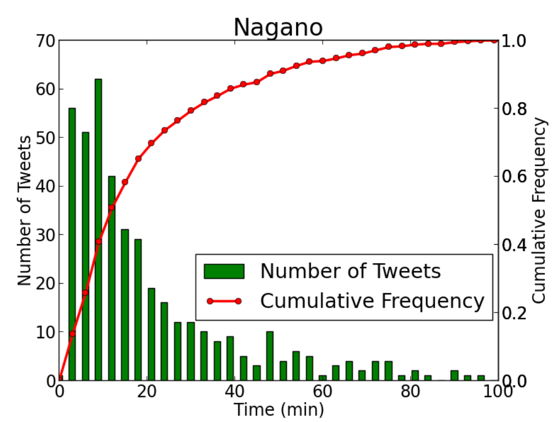

Figure 3: Time variations of tweets that refer to telephony failures

We considered cumulative frequency because the number of samples was small. The time variation of cumulative frequency is similar to the cumulative distribution function of an exponential distribution. This trend is also the same for earthquakes that occurred in Hokkaido and Ibaraki in 2014. Therefore, we fit each time variation of a cumulative frequency to the cumulative distribution function of exponential distributions so that we could determine a certain threshold to discard tweets. This cumulative distribution function is defined as

$$f(x) = 1 - e^{-\lambda x} \quad (2)$$

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

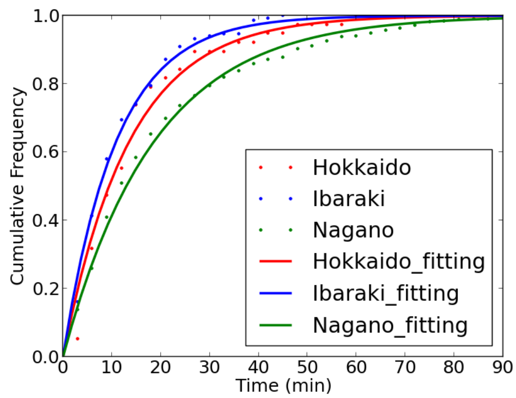

Figure 4: Results of fitting cumulative distribution functions of exponential distribution

The results showed that time variations of cumulative frequencies can be fitted to the cumulative distribution functions of an exponential distribution in all cases. Since this is an exponential distribution, we can detect 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

We judged the contents of the tweets detected using the candidate data detection method to filter out tweets reporting telephony failures. When our system detects telephone problems, we want to classify whether users could not make a call to the detected location or users could not call from the detected location. Figure 5 shows examples of tweets that were detected using the candidate data detection method.

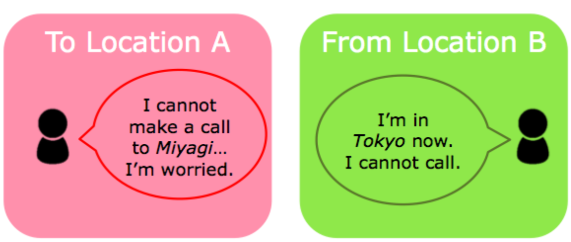

Figure 5: Examples of tweets detected using candidate data detection method

The left tweet shows that the user could not make a call to the detected location (Miyagi), while the right tweet shows that the user could not call from the detected location (Tokyo). Therefore, these tweets are different types and must be distinguished from each other.

We chose tweets not in Location B but in Location A because a failure was likely to occur in Location A. It was possible to filter out tweets with information on location associated with failures in this way. To distinguish between these tweets, we developed a method that uses machine learning.

5.1 Machine Learning Filter Method

First, we used the candidate data detection method and collected the tweets obtained from keyword search for each item of location information. For each detected location, we then classified the tweets into those of Location A or other tweets. To classify, we created a classifier using a support vector machine (SVM); SVM-light [27] with a default linear kernel. In the classification with machine learning, we used only Bag of Words (BoW) and rules as features. The BoW uses the occurrence of each word in a tweet as a feature, which is commonly used. We defined subjects of BoW as all parts of speech and only nouns, verbs, and adjectives. When rules are added as features, the subject of BoW are only nouns, verbs, and adjectives. The rules are:

1. words in the person or family dictionary are in the tweet
2. cannot make a call to (the detected location) is in the tweet

The person or family dictionary includes words related to people, e.g., mother, son, and sister. We selected these rules because tweets of Location A often satisfied any one of these rules.

5.2 Experiments and Results

We used tweets detected using the candidate data detection method from the corpus of tweets from the Great East Japan Earthquake as a training set. The set was made up of 1,746 tweets of Location A and 858 other tweets. We used leave-one-out cross validation as an assay method. Table 2 lists the results of the machine learning filter method.

Table 2: Evaluation of machine learning filter method

Method	Precision [%]	Recall [%]	F-value [%]
Subject of BoW is all parts of speech	80.76	96.85	88.08
Subjects of BoW are nouns, verbs, and adjectives	84.84	97.37	90.67
Rules are added as features	86.06	98.62	91.91

When the subjects of BoW are only nouns, verbs, and adjectives, the F-value increases compared with all parts of speech. This is because words that appear many times but do not affect the classification are eliminated. Moreover, adding the rules as features can increase the F-value, which suggests that adding rules is effective. Therefore, we were able to show that our proposed system performed well in terms of location classification.

6. DEGREE OF SIGNIFICANCE CALCULATION OF LOCATION INFORMATION

During the Great East Japan Earthquake, it was difficult to efficiently manage area recovery such as determining recovery priorities for networks and systems. To prioritize locations, we calculated the degree of significance, which has three indicators.

1. Tweet Rate of Telephony Failure
2. Seismic Intensity
3. Tweet Increasing Rate

For indicator 1, we obtained the ratio of tweets with information on location associated with telephony failures to tweets classified into each location group using the results from the location classification method discussed in Section 5. For indicator 2, we predicted seismic intensity in the detected locations using external information such as earthquake early warnings issued by the Japan Meteorological Agency. For indicator 3, we examined the rate of increase in tweets in emergencies compared with those during normal periods. We prioritized locations using these indicators. The degree of significance is calculated as follows.

1. For each indicator, the highest value among detected locations is set to 1, and values of other detected locations are normalized on the basis of the highest one.
2. For each locations, the average of the three normalized values is calculated.

Figure 6 shows time variations of the number of tweets in each prefecture during the earthquake, and Figure 7 shows the results of the degree of significance in each prefecture during the earthquake. The numbers in Figure 7 show recovery priorities.

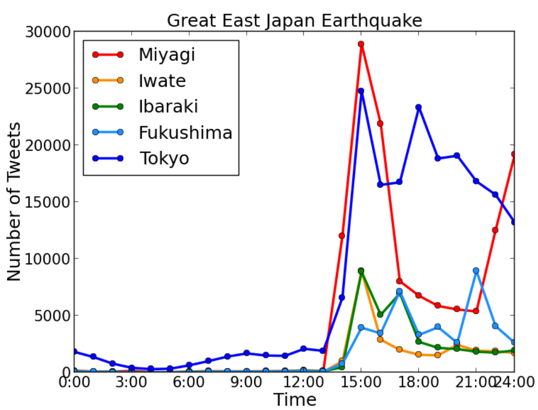

Figure 6: Time variations of number of tweets in each prefecture during Great East Japan Earthquake

As shown in Figure 6, the number of tweets in all areas increased rapidly. The number of tweets in Miyagi Prefecture, the seismic center of the earthquake, was large. However, the number of tweets in Tokyo Prefecture was also large, which should always be so because Tokyo is the principal city in Japan. Therefore, it is difficult to prioritize locations only from the number of tweets from this graph. On the other hand, as shown in Figure 7, the degree of significance in Tokyo Prefecture was smaller than in other locations. Therefore, locations with many tweets do not necessarily have high priorities. Locations with extensive damage, such as Miyagi and Iwate Prefectures, were highly prioritized. Therefore, we can prioritize locations by calculating the degree of significance using the three indicators.

Figure 7: Degree of significance in each prefecture during Great East Japan Earthquake

7. NETWORK CONTROL SYSTEM BASED ON SNS ANALYSIS

We constructed a network control system to automatically and autonomically optimize network traffic using information on telecommunications network conditions detected with our proposed system. We developed our control system on a network system called FLARE [28] to perform route control. We also implemented our network control system on a wide-area network testbed called Japan Gigabit Network eXtreme (JGN-X) [29]. The details of our network control system were described in our other papers.

8. CONCLUSIONS

We proposed a system for performing automatic and autonomic network control on the basis of the collective intelligence of an SNS.

We first designed and prototyped our SNS-based network failure detection system. We then evaluated our system using data from the Great East Japan Earthquake. As a result, our system could detect telephony failures with a high degree of accuracy and correctly extract the locations of failures and availability of telephone connections. Moreover, we calculated the degree of significance of each location for network recovery. As a result, we confirmed that locations with extensive damages, such as Miyagi and Iwate Prefectures, were highly prioritized. Hence, by using these results, we can determine recovery priorities in emergencies.

Next, we integrated our SNS-based network failure detection system into a network control system. That is to say, we constructed a network control system using information on network conditions detected with our system.

For future work, we aim toward information detection for detecting more detailed situations for users and connects to enable control through SNS analysis.

9. ACKNOWLEDGMENTS

This work is partially supported by the Strategic Information and Communications R&D Promotion Programme

(SCOPE) and Core Research for Evolutionary Science and Technology (CREST).

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