QoE Control of Network using Collective Intelligence of SNS 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. We developed a network control system on a deeply programmable network (DPN) environment and implemented it on a wide-area network testbed.**

I. 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 above-mentioned problem, we propose a network failure detection system using information from outside a network that is complementary to network monitoring devices. The proposed system was developed on a deeply programmable network (DPN) environment called FLARE [28], [29] and implemented on a wide-area network testbed.

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 information on telephony failures even for a finely-divided part of cities.
2) By integrating our SNS-based network failure detection system into a network control system, we can automat-

ically and autonomically perform network control using the collective intelligence of SNSs.

The remainder of this paper is organized as follows. In Section II, we introduce related research studies and give an overview of our proposed system in Section III. In Section IV, we discuss the determination of initial keywords and a candidate data detection method. In Section V, we discuss the location classification method and the determination of the degree of impact to users in Section VI. In Section VII, we give an overview of our network control system using information detected with our network failure detection system. We conclude the paper in Section VIII with a brief summary and discuss future research directions.

II. Related Work

There are a number of methods for detecting disasters and other events occurring in the real world (earthquakes, landslides, fire, etc.) by analyzing the data from SNSs [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18]. Sakaki et al. [6] introduced a method for detecting earthquakes early and estimating their locations by considering each Twitter user as a sensor. The Ministry of Land, Infrastructure, Transport and Tourism of Japan [7] introduced a method for detecting the signs and occurrences of landslides early on the basis of tweets of area residents where a disaster is likely to occur. Our study differs from these previous studies in that they restricted their focus only to the occurrence of an event and did not focus on detecting more detailed information when large events occur. We focused on detecting network failures caused by large-scale disasters. Rudra et al. [12] presented a classification-summarization framework for disaster-specific situational information on Twitter. This study is similar to ours in that it was focused on extracting tweets about the situation in various areas and relief operations, which contribute to situational awareness. Varga et al. [14] proposed a method for recognizing problem reports and aid messages from tweets during large-scale disasters. This study is similar to ours in that it was focused on detecting a wide range of problems that require solving. Sakaki et al. [15] extracted driving information in non-disaster cases using the content of tweets that refer to the road conditions around drivers and location information from the tweets posted by them. This study is similar to ours in that it was focused on using extracted information to present to drivers. 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 extract information in detail, 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 correctly using only 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], [21], [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, and they try to find only the fact of a network failure, not to get information in detail. We focused on natural disasters and the results from a system that performs network control on the basis of detected information. Moreover, the previous studies were focused on detecting various types of network failures including telephony failures using tweets. Therefore, our study also differs from these previous ones in that more detailed information on telephony failures, such as the degree of impact to users, can be detected.

III. Overview of Proposed System

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

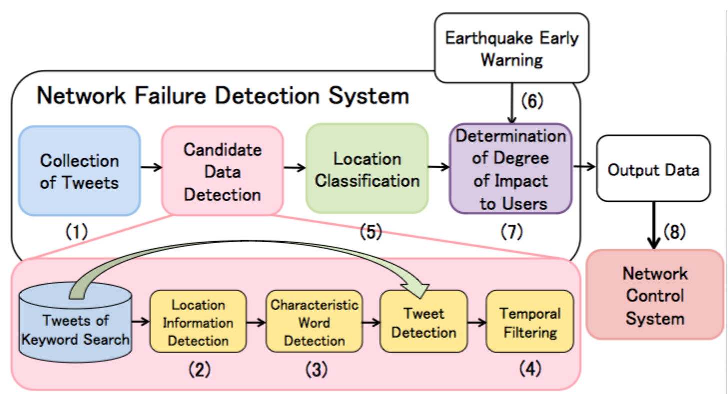


Fig. 1. Network failures detection system

The process flow of the proposed system is as follows. The numbers (1) - (8) are indicated in Figure 1.

(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).
(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 [23] issued by Japan Meteorological Agency, and obtain the time, position, and strength of the earthquake.
(7) Determine the degree of impact to users for a finely-divided part of cities.
(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.

IV. 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 I lists the details of the corpus, and example tweets in the corpus, which are translated from Japanese, are listed in Table II.

TABLE I
Corpus of tweets from Great East Japan Earthquake

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

TABLE II
Example tweets

- Earthquake! I felt the earth shake.
- There was a magnitude seven earthquake in Miyagi.
- Please prepare for the tsunami in Hachinohe-city.
- I found almost all things sold out at a convenience store.
- I'm anxious about my grandmother's safety.
- Yamanote Line has suspended operation.
- The power supply has been cut off in Morioka.
- I cannot call my mother in Iwate.

This corpus includes various types of tweets in addition to those about telephony failures.

A. Candidate Data Detection Method

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

1) Keyword Search: We set the initial keywords using a Search API [24] supported by Twitter Inc. to collect tweets regarding telephony failures. The details of the determination of initial keywords were described in our other papers [25].

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 [26], which separates sentences into a set of words. Latitude and longitude details of geotags were converted into city names using the Yahoo! reverseGeoCoder API [27] supported by Yahoo! Inc. We then classified the tweets of the keyword search in accordance with the detected location information into each location group.

3) Characteristic Word 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) 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 2 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.

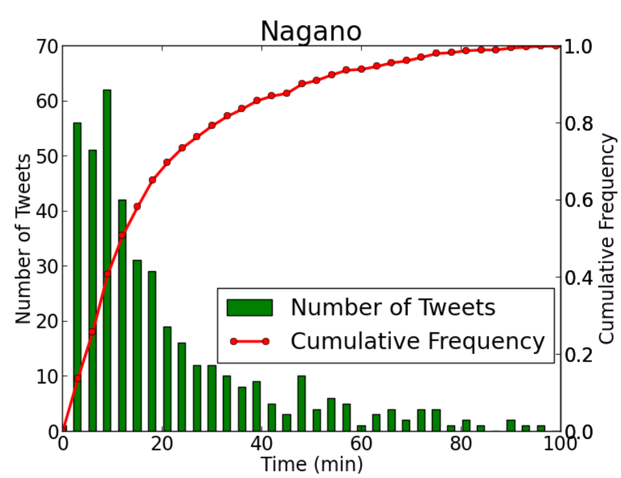


Fig. 2. Time variations of tweets that refer to telephony failures

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

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

Figure 3 shows the results of fitting earthquakes in Hokkaido, Ibaraki, and Nagano.

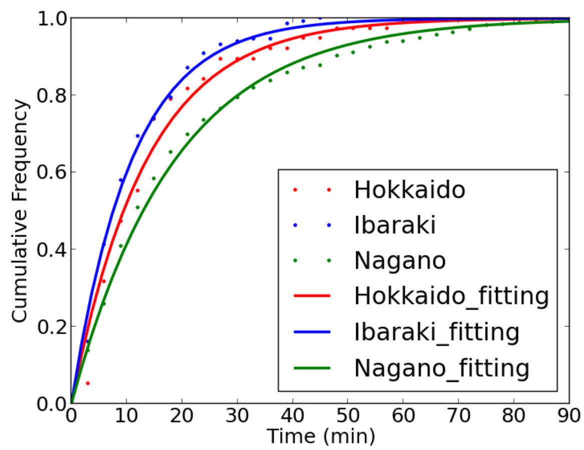


Fig. 3. Results of fitting cumulative distribution functions of exponential distribution

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 of our system when an earthquake occurs, we collect tweets every minute and use tweets in the last 60 minutes as potential tweets for failure detection.

B. Experiment and Results

In this section, we describe the evaluation and results of the candidate data detection method.

We used the methods discussed in Sections IV-A2, IV-A3, and IV-A4 for tweets obtained from the keyword search discussed in Section IV-A1 and collected the candidate data. At the same time, we manually collected correct tweets that reported telephony failures from all tweets obtained from the keyword search. The precision, recall, and F-value of the candidate data and correct tweets were then calculated.

We used three corpora of tweets from earthquakes that occurred in Hokkaido, Ibaraki, and Nagano in 2014. Table III lists the details of these corpora. In this table, the number of tweets represents those after the keyword search.

TABLE III
THREE CORPORA OF TWEETS FROM 2014 EARTHQUAKES

Dataset	Seismic Center	Date	Number of Tweets
A	Hokkaido	2014/07/08	184
B	Ibaraki	2014/09/16	566
C	Nagano	2014/11/22	808

Table IV lists the experimental results from the candidate data detection method. It is apparent that recall was not as high as precision because users sometimes posted very short tweets. Each F-value for all three earthquakes was around 85%, which is high. Therefore, we were able to show the efficiency of the candidate data detection method.

TABLE IV
PRECISION, RECALL, AND F-VALUE FOR DIFFERENT USES OF CORPORA

Dataset	Precision [%]	Recall [%]	F-value [%]
A	90.00	81.81	85.70
B	87.50	82.35	84.84
C	96.25	83.69	89.53

V. 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 4 shows examples of tweets that were detected using the candidate data detection method.

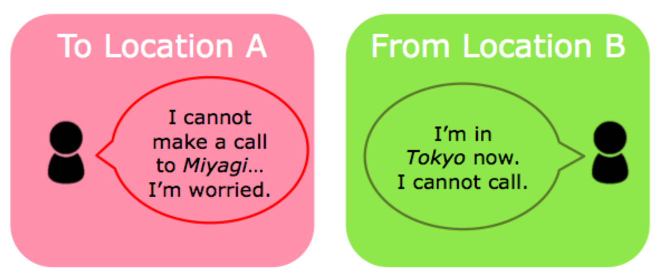


Fig. 4. Examples of tweets detected using candidate data detection method

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.

VI. Determination of Degree of Impact to Users for a Finely-Divided Part of Cities

Our approach was not able to determine only the propriety of connection of the telephone so far. Therefore, in this section, we detect more detailed information on telephony failures. Specifically, we determine the degree of impact to users for each small part of cities. These results can be used to manage efficient area recovery such as determining recovery priorities for networks and systems.

In this study, both tweets posted in case of emergency and ones posted during normal periods are analyzed. By grasping the distributions during normal periods, the degree of impact to users in case of emergency is determined. To determine the degree of impact to users, probability distributions were calculated using tweets posted during normal periods for each small part of cities. Figure 5 shows the probability distribution of Sendai city.

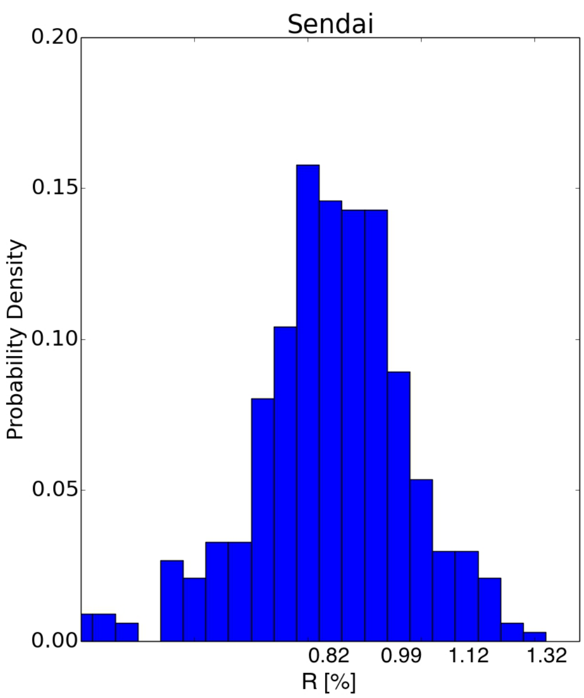


Fig. 5. Probability distributions of Sendai city

All tweets posted in 30 days when no failures were happened were divided into every one hour, so that 30*24 files were created. For each file, R was calculated as follows (equations (2)):

$$R = \frac{\text{the number of tweets information on a certain city appears}}{\text{the total number of tweets location information appears}} \tag{2}$$

The vertical axis of Figure 5 is the appearance frequency of R. Figure 5 shows that about 0.82% out of the total number of tweets location information appears were often appeared during normal periods in Sendai city. In this way, a probability distribution for each small part of cities was calculated using tweets posted during normal periods. Moreover, each probability distribution was fitted to the normal distribution. The normal distribution is defined as

$$f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} \int_{-\infty}^{\infty} \exp\left\{-\frac{(x-\mu)^2}{2\sigma^2}\right\} \mathrm{d}x \tag{3}$$

Here, μ is the average, and σ is the dispersion.

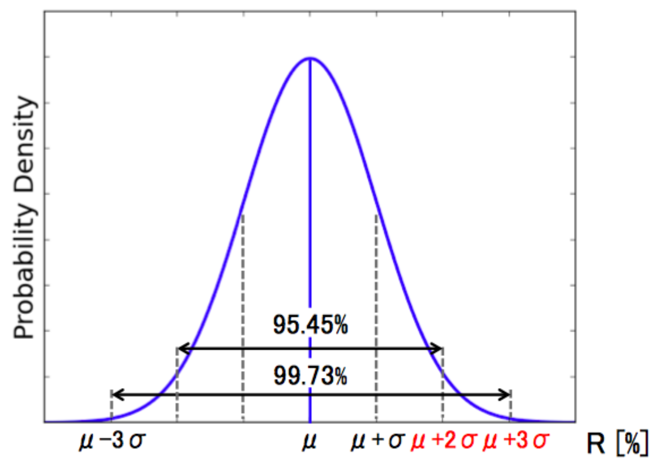


Fig. 6. Details of normal distribution

Next, each μ+2σ and μ+3σ was calculated from the normal distribution created for each cities. In a normal distribution, 95.45% and 99.74% of the entire event are covered up to each μ+2σ and μ+3σ, as shown in Figure 6. Therefore, R hardly exceed these values. If R exceeds these values in a certain city, some failures will be happened in the city since tweets are posted much more than usual. In this paper, $R_{emergency}$ for each cities was calculated using tweets about telephony failures in 60 minutes after the Great East Japan Earthqhake occurred. These tweets were detected by the location classification method in Section V. Next, $R_{emergency}$ was compared with μ+2σ and μ+3σ calcualted from the normal distribution. If $R_{emergency}$ exceeds either one, the city is determined to be abnormal.

Figure 7 shows the normal distribution of Sendai city. The red line shows the fitted normal distribution. If $R_{emergency}$ in Sendai city exceeds either 1.32% of μ+3σ or 1.12% of μ+2σ, the city is determined to be abnormal. In the Great East Japan Earthquake, $R_{emergency}$ in the city was 9.57%, and this was much more than the both values. Therefore, it was almost impossible for users to make a call to the city.

Figure 8 shows the results of the degree of impact to users of all cities. The red pins show cities where $R_{emergency}$ exceeds μ+3σ, and the yellow ones show cities where $R_{emergency}$ exceeds μ+2σ. Locations with extensive damage were determined that the degree of impact to users was large. Although locations with many tweets were also detected so far, this

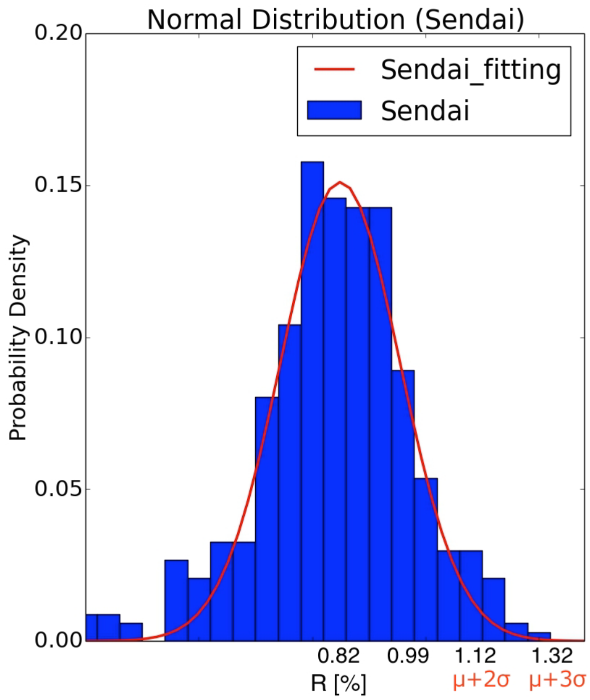


Fig. 7. Normal distribution of Sendai city

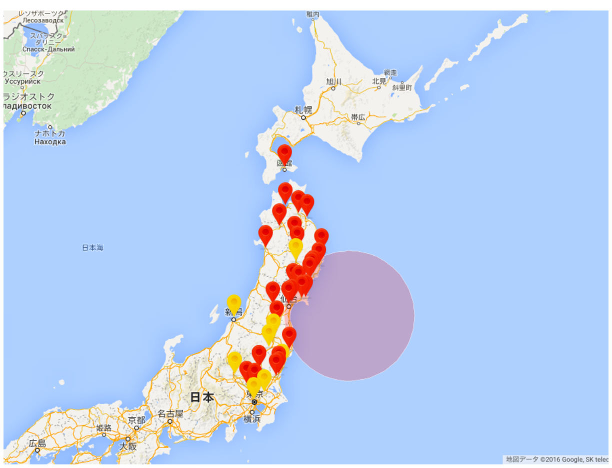


Fig. 8. Results of the degree of impact to users of all cities

method was able to detect only ones where users find it difficult to make a call.

VII. 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], [29] to perform route control. We also implemented our network control system on a wide-area network testbed called Japan Gigabit Network eXtreme (JGN-X) [30].

A. DPN/FLARE

A software defined network (SDN) that freely controls networks through programming is widely used. OpenFlow [31] is one of the technologies used to realize an SDN. Figure 9 shows an overview of OpenFlow.

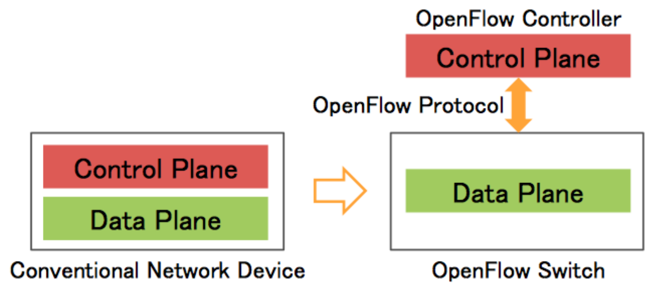


Fig. 9. Overview of OpenFlow

To appropriately transmit data on a network, a control plane that performs network control and a data plane that transmits packets according to the direction of the control plane are needed. Conventionally, they are built into each network device, and users are not able to extend the functions. However, they are separated in OpenFlow, and the control plane is programmable. Therefore, users can create programs and control network traffic freely without gaining direct access to hardware.

The OpenFlow controller shown in Figure 9 operates programmable software and centralizes route controls. The OpenFlow switch is controlled by the OpenFlow controller and transmits packets according to the direction. The OpenFlow protocol is an interface to connect the control plane and the data plane.

On the other hand, a deeply programmable network (DPN), in which both the control and data planes are constructed as programmable, has been proposed. Therefore, a DPN is an extension of an SDN. FLARE is one of the technologies used to realize a DPN. OpenFlow uses information of only the network layer and below, while FLARE uses information up to the application layer, which is not used by the SDN. Therefore, the data plane can also be managed, and it is possible to control it on the basis of the type of applications used if such applications are identified from the traffic. FLARE, which can use information about the application layer for control, is the most suitable platform because we focused on advanced and flexible network control. In this experiment, we have not fully used the function of FLARE that controls traffic based on information up to the application layer. In the future however, we aim toward the construction of a system that can perform more advanced and flexible network control on the basis of information extracted from social data.

B. JGN-X

The JGN-X is a large-scale network testbed for research and development, which is operated by the National Institute of Information and Communications Technology (NICT) [32]. With this testbed, it is possible to implement new generation network technologies in a near real-world environment. The JGN-X network has access points at 25 locations nationwide and 5 locations outside Japan, and wide-area networks inside and outside Japan have been constructed. The JGN-X network has FLARE switches at eight locations nationwide. We used some of them for this study.

C. Experimental Environment

We conducted an experiment using the architecture with FLARE, as shown in Figure 10. FLARE Central is a server for managing FLARE. The controller of the control plane was implemented on this server. The controller controls four FLARE switches in this experiment and performs routing. We integrated our proposed network failure detection system into FLARE Central. FLARE Central acquires and analyzes social data, and the controller gives control directions to each FLARE switch on the basis of the analysis results.

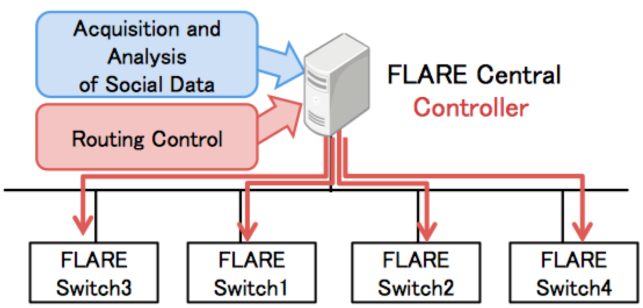
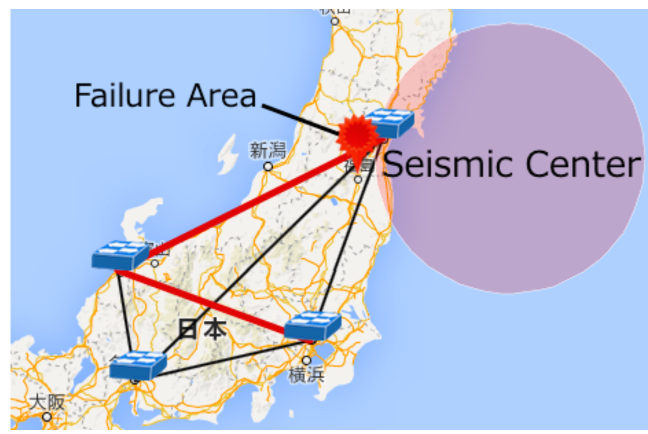


Fig. 10. Architecture with FLARE.

D. Routing Control based on Information of SNS

In this section, we present a use case of our network control system. The log data from the Great East Japan Earthquake was reproduced and a program that performs route control was validated on the JGN-X network as experimental conditions. Our network control system constructed using FLARE (Figure 10) was implemented on the testbed, as shown in Figure 11. We then operated a control program to automatically perform route control with information detected with our network failure detection system as a trigger. Specifically, the cost values of the routes between FLARE switches were updated in any one minute on the basis of the degree of impact to users discussed in Section VI. The cost values of the routes had a common default value. The optimum route that had the smallest cost value was searched using a Dijkstra method, and the route was set to the actual communication route. Figure 11 shows the results of route control based on data from the Great East Japan Earthquake.

(a) before earthquake



(b) after earthquake

Fig. 11. Results of route control

The red line shows the selected route between these two locations. After an earthquake, our system detects the failure area where users find it difficult to make a call, and the red line in Figure 11(a) is likely to be congested because the failure area is near the line. Therefore, the cost value of the line increases, and one of the red lines in Figure 11(b) becomes the smallest of all candidates eventually. The line is then switched from Figure 11(a) to Figure 11(b). Our network control system could perform automatic route control.

VIII. 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. Conventionally, telecommunications network conditions are monitored using network monitoring devices. However, when the Great East Japan Earthquake occurred, it was difficult to immediately grasp all such conditions using only information from network monitoring devices because the damage was considerably heavy and a severe congestion control state occurred. Therefore, we evaluated our system using data from this 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, to detect more detailed information on telephony failures, we determine the degree of impact to users for a finely-divided part of cities. As a result, we confirmed that locations with extensive damages were determined that the degree of impact to users was large. Although locations with many tweets were also detected so far, this method was able to detect only ones where users find it difficult to make a call.

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. In this study, a network system called FLARE was introduced for route control, and our network failure detection system was implemented on FLARE Central. We also used a wide-area network testbed called JGN-X and implemented our network control system constructed using FLARE on this testbed. We then operated a control program to perform route control. As a result, our network failure detection system successfully detected areas where users found it difficult to make a call and switched the communication routes passing near the areas to other optimum routes. Hence, automatic route control was achieved with our network control system.

For future work, we intend to evaluate our system using the other data set and indicate the effectiveness.

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