

재난 관련 위치 신뢰도 향상을 위한 소셜 미디어 활용

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Leveraging Social Media for Enriching Disaster related Location Trustiness

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[요 약]

위치기반 서비스는 재난 경보 시스템 및 추천시스템 등의 다양한 응용에서 중요한 역할을 한다. 이들 응용들은 위치정보(위도, 경도 등) 뿐만 아니라 위치에 대한 사건(지진, 태풍 등)의 영향력을 필요로 한다. 최근 이러한 위치에 대한 사건의 영향력을 제공하기 위해, 다양한 형태의 정보(지진 정보와 센서 정보)를 이용한 위치 신뢰도 계산 방법이 연구 되었다. 이전의 연구에서는 사건의 영향을 선형으로 감소시키는 형태로 위치 신뢰도를 계산하였다. 이 논문에서는 소셜 미디어를 추가적으로 활용하여 사건의 위치에 대한 영향력, 즉 위치 신뢰도를 향상 시키는 만드는 방법을 제안하였다. 우선 지진정보와 소셜 미디어 데이터를 수집하는 시스템을 설계하였다. 두번째로, 지진정보에 기반한 위치 신뢰도 계산 방법을 소개하였다. 최종적으로 소셜 미디어에 기반하여 공간적으로 분산되는 형태로 신뢰도를 증강시키는 방법을 통해 위치 신뢰도 정보를 더욱 풍부하게 제공하는 방법을 제안하였다.

[Abstract]

Location-based services play an important role in many applications such as disaster warning systems and recommendation systems. These applications often require not only location information (e.g., name, latitude, longitude, etc.) but also the impact of events (e.g., earthquake, typhoon, etc.) on locations. Recently, to provide the impact of an event on a location, how to calculate location trustiness by using multimodal information such as earthquake information and disaster sensor data is researched. In the previous approach, the linear decrement of impact value of an event is applied to obtain the location trustiness of a specific location. In this paper, we propose a new approach to enrich location trustiness, that is, the impact of an event on a location, by using social media information additionally. Firstly, we design a collecting system for earthquake information and social media data. Secondly, we present an approach of location trustiness calculation based on earthquake information. Finally, we propose a new approach to enrich location trustiness by augmenting the trustiness in spatially distributed manner based on social media.

색인어 : 재난 대응 네트워크, 재난 경보 시스템, 위치 신뢰도, 소셜 미디어

Key word : Disaster Resilient Networks, Disaster Warning Systems, Location Trustiness, Social Media

<http://dx.doi.org/10.9728/dcs.2017.18.3.567>



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Received 18 April 2017; Revised 29 May 2017

Accepted 25 June 2017

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1. Introduction

Location-based services (LBSs) have become popular and essential in many applications such as disaster warning systems and recommendation systems [1][2]. An LBS provides knowledge which can be used to infer the possible needs of a geographical location and to offer relevant services to satisfy these needs. For example, location information helps health-care center to decrease traveling time to the patient in case of emergencies. Indeed, if the precise location of a patient is known, a nearby care-giver can dispatch to that patient. In fact, however, many applications require not only location information by a given name or geo-location but also the impact of events (e.i. danger levels of an earthquake event) on that location. Therefore, calculating trustiness of a location for a specific event is the key problem for location-based services.

There are several researchers conducted about trustworthiness of information. The dynamic source routing (DSR) is modified in [3] so that the path with the highest trust is selected among those leading to the desired destination, instead of selecting the shortest path, to enhance security. To apply for wireless sensor networks, [4] focused on the way that trust information is combined with location-based routing protocols. [5] and [6] proposed the methods by using trust-based and location-based for social recommendation systems which predict the rating for user u on a nonrated item i or to generally recommend some items for the given user u by the ratings that have already existed. [5] presented CoTCoDepth that is a recommender system using limited knowledge and based on explicit user defined social relations whose scores are propagated in a P2P manner, while [6] proposed a model SocialMF - a matrix factorization based approach, which learns the latent feature vectors of users and items.

Recently, we have studied on location trustiness based multimodal information [7]. First, we proposed a model of trustiness calculation which described the impact of earthquakes using attributes like magnitude and location (latitude and longitude). Then, we extended the proposed method by using disaster sensor data for location trustiness calculation. To do this, we focused on analyzing the output signals of disaster sensors such as smoke sensor and temperature sensor. We then calculated the impact of disaster events based on feature data. Finally, a combined approach using both disaster information and sensor data is presented, which put a weight factor on each kind of trust value.

However, in our previous work, an assumption was made: The linear decrement of the impact of an earthquake occurrence, which is made by the distance from the epicenter to the boundary

of the disaster region, could partly affect the accuracy of location trustiness calculation. In this paper, we propose a new approach to enhance location trustiness calculation using disaster information and social media data. First, we design a system to collect earthquake information and social media data. Java-based techniques are able to implement programs to gather automatically (1) the earthquake information from the United States Geological Survey (USGS) site and (2) tweets related to earthquake events from Twitter. For the former, data with essential information including magnitude, time, longitude and latitude could be extracted. Regarding to the latter, after text; user location; place and geo-location are extracted, those information would be used as input of mining phase to obtain knowledge about danger levels of earthquake events which are mentioned in user's tweets. As far as we know, there is a lot of studies focusing on mining tweets data. However, it is not the focus of this paper, here, we assume that the danger levels of earthquake events can be found from tweets data.

After achieving disaster data, we investigate in constructing models for calculating location trustiness. Each kind of disaster data (earthquake information and tweet data) is used to construct an individual model. Then, we combine them to make a new model for enhancing the accuracy of location trustiness calculation.

The main contributions of this paper are briefly summarized as follows:

- We design a system to collect earthquake information from USGS site and tweet data from Twitter.
- We investigate in making a geo-mapping matrix (GMM) which is used to describe the impact of disaster events on the locations. We then define the location trustiness based on disaster information and GMM
- We present an approach of location trustiness calculation based on earthquake information.
- We propose a new approach to enhance the accuracy of location trustiness calculation by using social media data.
- We conduct two simulations based on location trustiness: disaster resilient network and disaster warning notification system. The results show that: (1) location trustiness based disaster resilient network reduces the time of recovering the network significantly with links/devices failure; (2) combining disaster information and social media data benefits users selection in disaster warning notification system.

The rest of this paper is organized as follows. Section II shows the related works. In Section III, we present the architecture of our system design. Section IV depicts our method for calculating location trustiness using disaster information. Our approach for enhancing location trustiness calculation is

presented in Section V. In Section VI, we evaluate the performance of location trustiness based applications by two real-life case studies. Finally, we conclude this paper and discuss future works in Section VII.

II. Related Works

The impact of a disaster has been calculated by the applications that collect disaster information such as magnitude and location of an earthquake event, then apply calculation models by using those parameters. There are several researches about the methods to calculate the impact of disaster [8-10]. In [8], the authors used Hazard map to determine three elements related to disaster. The first is the finding of possible risky zones. These possible location of fiber map are located by superimposing the transportation map on a network graph. Then they match the Hazard map and fiber map to find vulnerable parts of the networks and define the risk of traversing connections through these vulnerable parts in case of a disaster. The second and third element are probability of disaster and probability of damage, these depend on the type of disaster and network equipment's dimension, specification, and distance from epicenter.

In some cases, the region failure models adopted in available studies can be indicated by a kind of "deterministic" failure models. In fact, any component falling within the failure region will be destroyed, but they fail to reflect some important behaviors of physical attacks or natural disasters, where a network component only fails with certain probabilities, which lead to the vary of both distances to its epicenter and its dimension. Achille Pattavina et al. [9] believe that a probabilistic region failure model, which address by these properties, is suitable for network vulnerability assessment, so they consider a probabilistic failure model and apply it for the network vulnerability assessment.

Eytan Modiano et al [10] explores the inefficient of bipartite model of nodes location in the continent. Therefore, they relax the bipartite graph and vertical cut assumption by considering general model where nodes can be arbitrarily located on the plane. The authors consider modeling disaster in the network graph and circular areas in which the links and nodes are affected. These problems can be used to study the impact of disaster such as EMP attack and tornadoes more realistically.

Another common research topic on LBS for disasters management is that how to use social media data to indicate the affecting emergency level an area in a disaster situation. The

authors from article [11] have pointed out that users' location of a specific tweet could be identified by the definition "local words", which are frequently used in some specific areas. To improve the location estimation accuracy of article [11], the type of the tweets (original or replied ones) and historical tweets of the tweeting users are suggested to be used by the article [12]'s authors. They stated that there are many tweets made for answering the source tweets, and they might be not relevant, so there should be a method for solving them.

The general idea of articles [13-14] is the place estimating method should be made based on the sample data source: each term in the training samples would belong to a specific location whose position is known; so separating the input tweet could help the position estimation. The drawback here is they employ only the Twitter source, which could reduce the accuracy of the place estimation result. Worse yet, while their scopes are very large, our target only focuses on a small area: disaster, so applying their method would not be efficient here.

In [13], the authors indicate that occurring disasters' place should not only be designated from users' current locations, but also from the places which were mentioned in users' tweets. For instance: a person from Seoul could make a tweet about the storm happening in Busan, so the place of disaster must not be Seoul anymore. In order to find the exact occurring place, the authors also mention the correlations between a specific tweet and external context like established information from detected locations. This method is useful in the case which there are many possible places to be detected, and choosing the most suitable one would be challenging.

In [14], the authors assign each tweet with a known coordinates location. Then they suppose an algorithm to calculate the weights of these places, by the geographic distribution of users taken from Twitter user distribution. This idea comes from an assumption that there are fewer so-called "social sensors" in the place where there are fewer Twitters users reside. As a consequence, their probabilities of making a tweet would be much less here. However, if a tweet is created in this area, it would be much valuable. Those weights with their location are used to determine where the center of the disaster is, and also the awareness of each specific location.

III. Overview of System Design

The system is designed for real-time collecting and processing disaster data to obtain the trustiness of locations which is used by applications such as disaster resilient network system or disaster

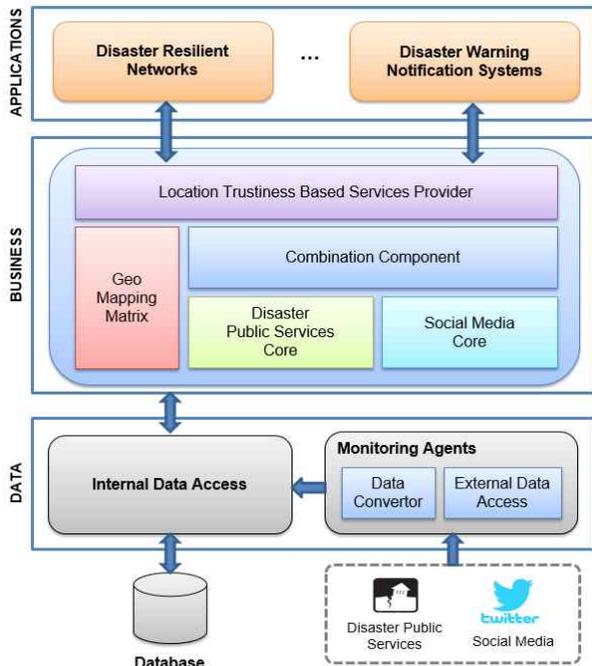


그림 1. 시스템 설계 개요

Fig. 1. The overview of the design of our system

warning notification systems. There are 3 layers in our design: data, business, and applications, as shown in Figure 1.

Data Layer: In this layer, we first design a Monitoring Agent component which is used to connect to the outside database and automatically gather disaster information from the public services or tweets related to disasters from Twitter, by a so-called External Data Access sub-component. In the latter work, the data is extracted by Data Converter to select the necessary disaster information. For example, the system only extracted the essential earthquake information from USGS site, including magnitude, time, longitude, and latitude.

Next, we design an Internal Data Access component to make the connection to the database in MySQL server. In this component, we provide the stored procedures for querying database. The component communicates with Monitoring Agents component to retrieve the disaster data that is extracted from other services. It also communicates with other components in Business Layer to provide the information for calculating trustiness of location.

Business Layer: This layer contains major components of location trustiness calculation. It consists of (1) a component defining a Geo-mapping matrix, (2) a Disaster Public Services Core component which is responsible for calculating trustiness of location based on data from other disaster public services, (3) a Social Media Core component for processing tweets data, and (4) a Combination Component which provides the final trustiness of location based on the trusted value from both disaster information

and social media data. Besides, we design a Location Trustiness Based Services Provider for communicating with other applications which would use the trustiness of location for different purposes.

Application Layer: This layer would be designed by other systems which need location trustiness from our service. We will presents more details in two applications: disaster resilient network and disaster warning notification system in Section VI.

In the next sections, we will dig deep into how to calculate and enhance the location trustiness using disaster information and social media data.

IV. Location Trustiness with Disaster Information

In this section, we present an approach to calculate trustiness of location using disaster information. To do this, we define a geo-mapping matrix (GMM), then we calculate the impact of disaster event on each affected cell of GMM.

A GMM is defined by a matrix which covers a specific region, for instance, the development area of a physical network. That is a set of locations $L = [L_{ij}]_{n \times m}$, where each location L_{ij} is a square with size equals $c \times c$, and c can be a real number describing the length by kilometer.

We define a trustiness matrix $T = [T_{ij}]_{n \times m}$ which describes the impact of disaster events on affected location of L , where T_{ij} denotes the trustiness of location $L_{i,j}$, which is defined as below.

Definition 1: The trustiness of location (or location trustiness) is a real number in the range from 0.0 to 1.0 that indicates the likelihood of the impact of disaster events on a cell in GMM.

Thus, if the trustiness of location (trust value) is equal to 0, it means the location may be seriously affected by disaster (no trust). Otherwise, if trust value equals 1 mean that the location could be out of affected region (full trust).

Our approach for calculating trustiness of location based on earthquake information is as follows: (1) find Possible Region Affected (cells) on the GMM where earthquake event e_i happened and (2) calculate trustiness of location for those cells. Note that, the current trustiness of a location is calculated by both of current disaster event and historical disaster events that affected to the same cell on the GMM.

To find Possible Region Affected (PRA), we used an equation in our previous work [7], which shows the relationship between moment magnitude and surface rupture length of an earthquake event as follows:

$$L_R = 10^{(0.862069 * M - 4.37931)} \tag{1}$$

where M is the magnitude ($M \geq 5.7$) and L_R is the surface rupture length of the earthquake. Thus, the size of PRA is $K \times K$, with K is the minimum number of odd integer satisfying $K \geq L_R/c$, where c is the unit length of $L_{i,j}$. In our approach, the impact of an earthquake is decreasing linearly with the distance from the epicenter to a location. We formulate the effect of an earthquake at each cell in PRA as follows:

$$T_d = \begin{cases} 1 - \frac{M}{\delta} & \text{if } d = 0 \\ T_{d-1} + \frac{M}{\delta \times R} & \text{if } d > 0 \end{cases} \tag{2}$$

where d is an integers number that shows the distance by cells from epicenter cell ($d = 0$) to R on the GMM, R is an integer number and $R = K/2 + 1$, δ is a threshold of magnitude to set trustiness value to be equal to 0 ($M \leq \delta$).

In practice, a location $L_{i,j}$ can be affected by a set of earthquake events $e = \{e_1, e_2, \dots, e_n\}$. Thus, before the earthquake event e_n happened, $L_{i,j}$ has a trust value equals T_{ij}^n . To calculate T_{ij}^n , our approach based on averaging trustiness value of that cell as follows:

$$T_{ij}^n = \frac{n-1}{n} \times T_{ij}^{n-1} + \frac{1}{n} \times t_{ij}^{e_n} \tag{3}$$

where $t_{ij}^{e_n}$ is the trust value at the location L_{ij} caused by only earthquake event e_n .

As we mentioned before, The linear decrement of the impact of an earthquake occurrence, which is made by the distance from the epicenter to the border of the disaster region, could partly affect the accuracy of location trustiness calculation. In the next section, we propose a new approach to enhance location trustiness calculation by using social media data and combining with the trusted value which is calculated using disaster information.

V. Enhancing Location Trustiness with Social Media

The general idea is the typical effects of earthquakes of various magnitudes near the epicenter are categorized into some levels.

표 1. 지진 영향 분류

Table 1. Category of the impact of an earthquake

Level	Name	Description
1	Minor	Felt by people, but very rarely causes damage.
2	Light	Some objects may fall off shelves or be knocked over.
3	Moderate	Can cause damage of varying severity to poorly constructed buildings.
4	Strong	Damage to a moderate number of well-built structures in populated areas
5	Major	Causes damage to most buildings
6	Great	Major damage to buildings, structures likely to be destroyed.

Then, mining data techniques are used to classify tweets, which are collected during the earthquakes duration, into corresponding levels. Finally, we propose a model for calculating location trustiness based on categorized tweets.

First, we categorized the impact of an earthquake event into 6 levels based on the typical effects of earthquakes of various magnitudes near the epicenter which are obtained in [15]. Table 1 shows the levels of the impact of the earthquakes with trusted value.

As shown in Table 1, we consider to the effects of earthquake which can be felt by people, or can be estimated by damage to buildings and structures.

Supposing that we have obtained tweets which mention about locations (cells) on the GMM, where are affected by an earthquake event. To specify tweets belong to a location, we could use their attributes such as place, geo or text. We assume that, these tweets can be categorized into levels as in Table 1.

We then consider calculating trustiness of a location, L_{ij} . Let $C_k(i, j)$ is the number of tweets at level k at location L_{ij} , and ε_k is the real number ($0 \leq \varepsilon_k \leq 1$) indicating the danger level of earthquake at level k ($1 \leq k \leq 6$). It is possible to find that a tweet at higher level has a greater of ε_k . By default, we set $\varepsilon_1 = 0.1, \varepsilon_2 = 0.2, \varepsilon_3 = 0.4, \varepsilon_4 = 0.6, \varepsilon_5 = 0.8, \varepsilon_6 = 1.0$. These values could be adjusted to be more suitable in a particular disaster situations. Thus, we can formulate location trustiness calculation using social media data as follows:

$$T_{ij} = 1 - \frac{\sum_{k=1}^6 \varepsilon_k C_k(i, j)}{\sum_{k=1}^6 C_k(i, j)} \tag{4}$$

To enhance the accuracy of location trustiness for each affected location we combine trust value of two approaches: using disaster information and social media data. To do this, we define

T_D is the trustiness of location which is calculated by disaster information such as earthquake events, T_S is the trustiness of location using social media data, which is calculated by using Equation 4. Now, the final trustiness of location T_L on a cell is defined as follows:

$$T_L = w_D T_D + w_S T_S \tag{5}$$

where w_D is the weighted of T_D , w_S is the weighted of T_S , and $w_D + w_S = 1.0$

VI. Applications of Location Trustiness

6-1 Disaster Resilient Network

Assume that, we had a network topology that connects many cities together in Korea, it includes 40 nodes and 128 links. Each node and link had an ID stored in the database and a location reference to the map. We assume that an earthquake signal with 7 richter degree of magnitude occur at a specific location on the map. We can calculate the trustiness of vulnerable area by using our method in the previous sections. The effect from earthquake makes a part of network go down, so we can calculate the trustiness and estimate the list of link failure.

We used Mininet tool to simulate the above network and OpenDayLight as the controller. In additional, we setup randomly the delay value of each link between two nodes from 1 to 20 milliseconds to make a different throughput for each path. In this paper, we measure the throughput and recover time of network when disasters occur to evaluate the response time of baseline method and our so-called “Location Trustiness Based Network Recovery” method.

To evaluate the throughput of each path in the network, we install Iperf in two hosts at the starting point and end point of a path, then we measure throughput of network between two hosts in a short of period time. This measuring indicates the throughput and recovery time of network showed at Fig. 2. Actually, when the change of network status; such as link down or failure of switch; is experienced, the controller will setup a new flow to switch to, to ensure the connectivity. The problem is how to select a good flow in a short time.

In our system, we provide *Geo-mapping matrix* and *Disaster Public Services Core* to calculate the trustiness of location based on data from disaster. As a consequence, we can estimate the list of link failure in the network, which helps our system to have a global view of the network. It is possible to pick a new available

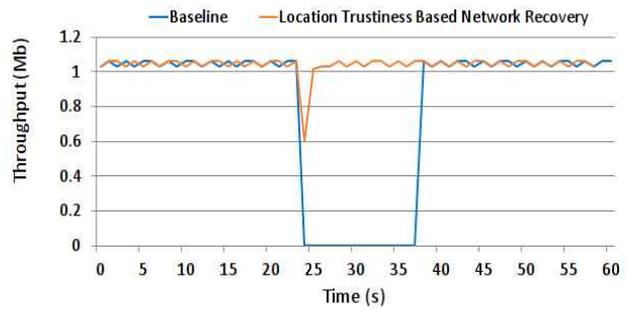


그림 2. 재난 상황에서 처리량 측정

Fig. 2. Throughput measurement under a disaster event

path in backup table and setup this path to the network when having the change of network status. In case of the baseline method, the system is ambiguous about the nodes and links failure. It would pick a next flow in backup table and setup to the network, and it waits for response from node about the status. If that flow includes a link failure, it will continue picking a next flow and setup to the network. This progress will continue until it meets an available flow.

The result of two above methods are illustrated in Fig. 2 with throughput and active time parameters. The Baseline draw the throughput lower than ours at the time disaster events happen. Because our system has a global view of network, it can predict the next appropriate flow to setup, so the throughput is higher than Baseline at the same time. Also, it saves time to recover the network connectivity when disaster happens. We can see the result in Fig. 2, our method recover the connectivity of network at second 23' instead of second 37' in the baseline method.

6-2 User Selection in Disaster Notification System

In this section, we conduct simulations of users selection in a disaster warning notification systems [17]. It should have a right strategy to select users affected by disaster: the users live in higher danger levels should be selected to be notified earlier than those from the lower ones, because a late or wrong choice could put the users into a dangerous situation. Therefore, location trustiness can be used as an important information source to support disaster warning notification system to optimize the number of users receiving notification message in time. So, the users living in location having a lower trust value will be selected to delivery message earlier than others.

We consider the warning message delivering system, which notifies the users who live in affected region caused by earthquake. These regions could be represented as a square matrix, m , in GMM as presented in previous sections. Each cell in matrix m has a trust value T_{ij} ($0 < T_{ij} < 1$), and there are p

people (users) who need warning messages about the dangerous situations happen in their location. We assume that the system have essential information of all users such as e-mail address, phone number, and geographic location. It is possible to understand that the more users locate near the epicenter, the shorter time they have to escape from treacherous location, the higher priority they should have, and the lower trustiness their locations should have. Let d be the distance by cells to the epicenter cell. We also assume that the users live in the same location (i.e. a cell in GMM) have the same needed time, t_n , which is the time interval since the earthquake happened, to escape dangerous situation. In practice, t_n depends on the danger level of the earthquake, which is reflected through location trustiness. It also depends on the distance to the epicenter of an earthquake event. We know of no simple way to estimate the value for t_n . We therefore use an adaptive heuristic for estimating needed time for users to get out of dangerous situations. In our simulation, the needed time is estimated as follows.

$$t_n(i, j) = \alpha_d \times T_{ij} \times (2d + 1)^2 \quad (5)$$

where α_d is tuning parameter, and the locations with different d has a different value of α_d . α_d of two earthquake events whose values of magnitude are different would be different.

Another parameter S , the message sending speed of the system, also plays an important role in increasing the number users receiving notification message in time. A disaster notification system can send up to a few hundreds of messages per minutes (e.g. ALERiTY [16] can send up to 250,000 messages, including text notifications; voice calls; emails and desktop alerts, per minute).

We simulate the messages delivery of a disaster warning notification system in two strategies: *Random way strategy* and *Location trustiness based strategy*. In *Random way strategy*, the messages delivery is performed with random locations/users, while *Location trustiness based strategy* performs messages delivery sequently from the epicenter location to the boundary of affected region, and from lower location trustiness to higher ones. We assume that the affected regions have population density around 500,000 people/ km^2 in average, and 60% of people can receive message from a disaster warning notification system.

Fig. 3 illustrates the difference rates of messages delivered in time with different magnitudes. From magnitude of 5.7 to 6.3 degree, the rate of messages delivered in time remains 100% for both of 2 methods. However, from 6.3 to 6.6; while the rate of

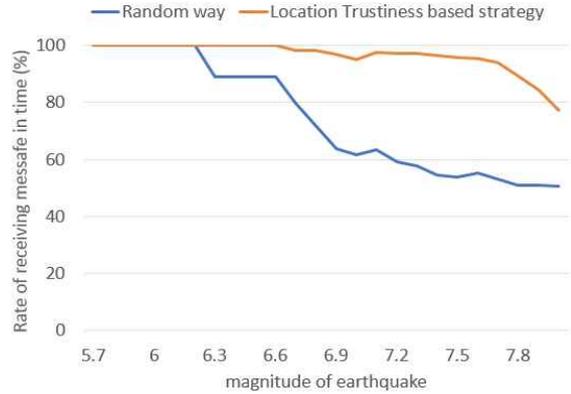


그림 3. 다양한 규모에 대해 메시지 전송률 비교

Fig. 3. Comparison of the rate of receiving messages in time with various of magnitude.

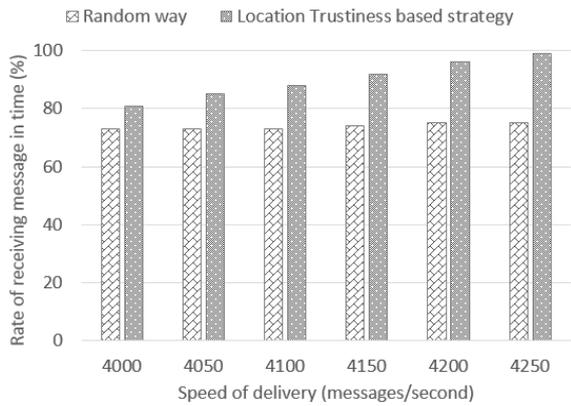


그림 4. 다양한 메시지 전송속도에 따른 메시지 전송률 비교

Fig. 4. Comparison of the rate of delivery messages in time with various of message sending speed.

in-time-messages sent by Location trustiness based strategy stays at nearly 100%, the one sent by Random way decreases to around 90%. And in the final stage; which starts from 6.6 degree of magnitude to 8.0; the former one, which decreases to only nearly 80%, out-performs the latter one, which sinks to nearly 50%.

In Fig. 4, the difference rates of messages delivered in time of the 2 compared methods are compared with different messages sending speed. It could be seen that with the increasing of delivery speed, while the rate of message sent in-time by the “Random way” rises marginally, the one performed by our method increases significantly, reaching nearly 100% at the speed of 4250 messages per second.

VII. Conclusion

In this paper, we proposed a new approach to enhance location trustiness calculation using disaster information and social media

data. We designed a system to collect earthquake information and tweets related to earthquake events. We then proposed an approach to calculate location trustiness based on earthquake information. To enhance location trustiness calculation, we proposed additional approach for estimating location trustiness by using tweets data. We combined two approaches to make the trust value close to the reality of disaster situations. We also presented applications of location trustiness in two case studies: a disaster resilient network and a disaster warning notification system. The experimental results depicted that: location trustiness based disaster resilient network reduced significantly the time of recovering the network with large scale links/devices failure; and a disaster warning notification system with location trustiness can send a message to users more effectively by considering priorities of users for receiving messages.

Acknowledgment

This research was supported by the MSIP(Ministry of Science, ICT and Future Planning), Korea, under the ITRC(Information Technology Research Center) support program (IITP-2017-2016-0-00314) supervised by the IITP(Institute for Information & communications Technology Promotion)

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