ABSTRACT

When a large-scale natural disaster occurs, it is necessary to quickly collect damage information so that disaster-relief operations and wide-area support in accordance with the scale of the natural disaster can be initiated. Previously, we proposed a fast spatio-temporal similarity search method (called the ST-Sim method) that searches a database storing many scenarios of disaster simulation data represented by timeseries grid data for scenarios similar to insufficient observed data sent from sensors. When the ST-Sim method is naively applied for estimating disasters occurring at multiple locations, e.g., fire spreading after a large-scale earthquake, it must prepare a huge number of combinations consisting of scenarios that represent disasters at multiple locations. This paper presents a combination method of simulation data in order to apply the ST-Sim method for estimating disasters occurring at multiple locations. This proposed method stores scenarios, each of which represents a disaster occurring at a single location, to a database; thus, reducing the number of scenarios. After a disaster occurs, it extracts and composes scenarios similar to observed data, resulting in efficient disaster estimation in any situation. We conducted performance evaluations under the assumption that an earthquake occurs below the Tokyo metropolitan region and estimating the spread of fire in the initial response. These results of the processing time for estimating the spread of fire show that the processing time is within 30 minutes, which is practical.

Keywords

disaster management, spatio-temporal database, spatio-temporal similarity search

1. INTRODUCTION

Japan is located in the “Circum-Pacific Mobile Belt,” where seismic and volcanic activities occur constantly [1]. Although the country covers only 0.25% of the land area on the planet, it experiences a high number of earthquakes and has many active volcanoes. Due to its geographical, topographical, and meteorological conditions, Japan is subject to frequent natural disasters such as typhoons, torrential rains, and heavy snow. Consequently, such natural disasters can result in a large loss of life and significantly damage property. Examples of recent large-scale natural disasters that caused immense damage are the Great East Japan Earthquake (March 2011), landslides in Hiroshima Prefecture (August 2014), volcanic eruption of Mt. Ontake (September 2014), and Kumamoto earthquakes (April 2016). The probability of an M7-class earthquake occurring in the South Kanto area (around Tokyo) within 30 years is estimated to be 70%. If an earthquake directly hits the Tokyo metropolitan area, the human and material damage caused by collapsing buildings and the spread of fires will be extremely serious. Accordingly, it is a national priority to protect citizens’ lives, livelihoods, and property from large-scale natural disasters.

When a large-scale natural disaster occurs, damage information is collected during the “first action” period. After that, disaster-relief operations and support over a wide area (in accordance with the scale of the disaster) are requested. At present, to collect damage information, municipalities, cities, districts, towns, and villages report damage information to prefectural governments, which then report to the national government by e-mail or fax. Disaster-related organizations need a few days to grasp the damage situation of a large-scale natural disaster because they collect the damage information manually. Thus, the time taken to grasp the damage situation of large-scale natural disasters needs to be reduced.

During a large-scale natural disaster, disaster-related organizations obtain insufficient information because infrastructure, such as power networks and communications net-
works, become damaged. However, they still have to estimate the damage situation of a large-scale natural disaster from that insufficient information. In particular, disaster-related organizations need to quickly obtain information on the coverage of the natural disaster. Therefore, they can plan where to dispatch rescue teams and disaster relief. Recently, simulation technologies for simulating tsunami, spreading fires, heavy rain, and so on have made it possible to estimate the coverage of a natural disaster.

After a large-scale natural disaster occurs, a natural disaster simulation is run to estimate the disaster’s effect. Input conditions are necessary to run the natural disaster simulation. However, there are cases in which the input conditions are not collected after a large-scale natural disaster occurs. For example, a fire-spreading simulation is run to estimate the damage caused by fire after a large earthquake occurs directly below an urban area. Information on fire-outbreak points, wind directions, and wind velocities is necessary as input conditions, but information on fire-outbreak points is difficult to collect. Even if input conditions are collected, there are some cases in which the processing time for simulating a natural disaster is too long. For example, tsunami simulators take much time to simulate tsunami coverage because they calculate complicated tidal wave propagation. To solve these problems, one approach is to estimate the coverage of a natural disaster by searching a database storing many scenarios of disaster simulation data represented by timeseries grid data for scenarios similar to insufficient observed data sent from sensors after the disaster occurred. On the basis of similar scenarios, the disaster situation can be estimated in places where sensors do not exist or sensors cannot send observed data, and a future disaster situation can be predicted. The processing time for performing a spatio-temporal similarity search becomes long because the amount of disaster simulation data is generally enormous.

We previously presented a fast spatio-temporal similarity search method (called the STSim method) [6] that searches a database storing many scenarios of disaster simulation results represented by timeseries grid data for scenarios similar to observed data. The STSim method efficiently processes spatio-temporal intersection by using a spatio-temporal index to reduce the processing time for the spatio-temporal similarity search. It can be implemented on top of an existing relational database management system (RDBMS), which supports high-performance and reliable processing even if a large-scale natural disaster occurs. When the STSim method is naively applied for estimating disasters occurring at multiple locations, e.g., fire spread after a large-scale earthquake, it must prepare a large number of combinations consisting of scenarios that represent disasters at multiple locations.

This paper presents a composition method of simulation data in order to apply the STSim method for estimating disasters occurring at multiple locations. The proposed method stores scenarios, each of which represents a disaster occurring at a single location, to a database; thus, reducing the number of scenarios. After a disaster occurs, the proposed method extracts and composes scenarios similar to observed data, resulting in efficient disaster estimation in any situation. We conducted performance evaluations under the assumption of an earthquake occurring below the Tokyo metropolitan region and estimation of the spread of fire in the initial response. The results of the processing time for estimating the spread of fire show that the processing time is within 10 minutes, which is practical.

The remainder of this paper is organized as follows. Section 2 discusses related works, Section 3 describes the preliminaries, Section 4 presents the proposed method, and Section 5 analyzes the results of a performance evaluation of the proposed method. Finally, Section 6 concludes the paper by describing directions for future work.

2. RELATED WORKS

From the view point of applications, some kinds of researches to quickly and accurately grasp a damage situation by using information and communication technology (ICT) techniques including sensor and crowdsourcing techniques have been conducted [11, 15, 20, 21]. As these researches have been shown, it is considered to be important to use ICT techniques for grasping a damage situation when a large-scale disaster occurs. Our approach to grasp a damage situation is to use spatio-temporal database techniques. Concretely, our approach is to estimate the coverage of a natural disaster by searching a database storing many scenarios of disaster simulation data represented by timeseries grid data for scenarios similar to insufficient observed data sent from sensors after the disaster occurred.

Regarding research on a spatio-temporal database, many types of spatio-temporal indexing methods for moving objects that change their locations over time have been studied [14, 16]. The R-trees-based methods [3, 17, 19] and B-tree based methods [4, 10, 12, 22] were proposed to efficiently carry out spatio-temporal queries such as range query and k-nearest neighbor query. These methods are similar to our method in that moving objects (timeseries point data) are managed by using a spatio-temporal index. In particular, the B-tree-based methods [4, 10, 12, 22] have a similar approach to our method in managing moving objects efficiently. However, these methods differ from our method in that our method manages timeseries grid data by using a spatio-temporal index for an efficient spatio-temporal similarity search between timeseries grid data and observed data.

Regarding research on multi-dimensional databases, many mapping-based indexing methods have been studied. Mapping-based indexing maps multi-dimensional data into one-dimensional values with space-filling curves [8] (e.g., z-order curve and Hilbert curve) then indexes the values in a one-dimensional index structure (e.g., B*-tree). The one-dimensional index structure has been implemented in most existing RDBMSs. Therefore, mapping-based indexing can be implemented on top of an existing RDBMS without modifying the RDBMS. There are currently mapping-based indexing methods for spatial data [2, 6, 7, 9, 23], moving objects [4, 10, 12, 22], and multi-dimensional data [13]. These methods are similar to our method in that the mapping-based indexing approach is used for managing multi-dimensional data. However, these methods differ from our method in that our method aims to reduce the time for spatio-temporal similarity search between timeseries grid data and observed data.

3. PRELIMINARIES

3.1 Schema of Time-series Grid Data and Observed Data
Data structures of time-series grid data and observed data are defined in accordance with the relational data model [5] since the STSim method can be implemented on top of an existing RDBMS. For simplicity, the problem is set in two-dimensional space, i.e., xy space. However, the problem setting can be extended to three-dimensional space, i.e., xyz space.

The time-series grid data represents the coverage of a natural disaster, which has a number of scenarios. One scenario consists of a combination of initial conditions for simulating a natural disaster. The timeseries grid data returns values given by a scenario, time interval, and geometry. The relation of timeseries grid data is defined as \( R_s(SID, I, G, V) \), where \( SID \), \( I \), \( G \), and \( V \) represent scenario identification, time interval, geometry, and value corresponding to \( I \) and \( G \), respectively. The \( SID \) is an identification uniquely assigned to each simulation scenario; \( I \) includes a start-time instance, \( T_s \), and an end-time instance, \( T_e \); and \( G \) means the location and geometry of a cell composing a grid and includes four coordinates: \((X_1, Y_1), (X_2, Y_2), (X_3, Y_3), \) and \((X_4, Y_4)\). The \( V \) represents a value, i.e., a physical quantity (e.g., numeric data or string data) corresponding to \( I \) and \( G \). Depending on the coverage of a natural disaster, a number of physical quantities may exist. If the number of physical quantities is \( n \), the relation of timeseries grid data is defined as \( R_s(OID, I, G, V_1, ..., V_n) \). For simplicity, the number of physical quantities is taken as one.

The observed data represent a value observed by a sensor. The data provides the observed value in terms of a time interval and geometry. The relation of observed data is defined as \( R_s(OID, I, G, V) \), where \( OID \), \( I \), and \( G \) represent the identification of a sensor, time interval, and geometry. \( OID \) represents the identification uniquely assigned to each sensor; \( I \) includes a start-time instance, \( T_s \), and an end-time instance, \( T_e \); and \( G \) represents the location of a sensor. The location is represented by coordinate \((X, Y)\). \( V \) represents a value, i.e., a physical quantity (e.g., numeric data or string data) corresponding to \( I \) and \( G \).

3.2 Problem Setting

The STSim method [6] searches a database storing many scenarios of disaster simulation data represented by timeseries grid data for scenarios similar to observed data. It outputs scenarios just as the database stores them. On the other hand, the proposed composition method of simulation data outputs a new scenario by composing scenarios similar to observed data. The problem that this paper addresses is defined as follows.

Output a composed scenario similar to observed data
Input: \( R_s, R_s, I, G, V \)
Output: \( R_s(I, G, V) \)

Here, \( I \) represents a time interval of observed data, which is compared with time-series grid data stored in the database when scenarios similar to observed data are extracted. \( R_s \) represents a composed scenario represented by timeseries grid data, and \( I, G, \) and \( V \) included in \( R_s \) represent time interval, geometry, and value corresponding to \( I \) and \( G \), respectively.

Figure 1 shows an example of disaster estimation before and after applying simulation data composition. The database stores \( n \) scenarios of disaster simulation results. Before applying simulation data composition, Scenario 2, which is the most similar to observed data, is output. On the other hand, after applying simulation data composition, Scenarios 1 and 5 similar to observed data, are extracted, then the estimated results are output by composing Scenarios 1 and 5.

4. PROPOSED METHOD

The proposed method stores scenarios, each of which represents a disaster occurring at a single location, to a database; thus, reducing the number of scenarios. After a disaster occurs, the proposed method extracts and composes scenarios similar to observed data, resulting in efficient disaster estimation in any situation.

Figure 2 shows the procedure of the proposed method. The following subsections describe each step in detail.

4.1 Scenario Creation

Before a disaster occurs, “Scenario creation” involves running a disaster simulator based on the input conditions (parameters) and output scenarios represented by timeseries grid data. The input conditions are set based on exclusive knowledge about the disaster.

Input conditions (parameters) of a disaster simulation are defined by \( P = \{p_1, p_2, ..., p_k\} \). If the approach of simulation data composition is adopted, the number of input conditions are reduced to \( P' = \{p_k|P' < n, p_k \in P\} \). An example of scenario division is as follows. When the spread of fire is estimated, scenarios are stored in a database in the units of the input parameters, which include wind direction, wind speed, and multiple fire-point locations. In this case, the number of scenarios is enormous because the number of scenarios is \( \sum_{k=1}^{n} C_n \) when the number of high fire risk buildings is \( n \). On the other hand, when the scenario division approach is adopted, the number of scenarios is \( n \) because the scenarios are stored in a database in the units of input parameters, which include wind direction, wind speed, and single fire-point location.

4.2 Data Transformation and Load of Scenarios

“Data transformation and load of scenarios” involves storing scenarios output by the disaster simulator in a database based on timeseries grid schema, i.e., \( R_s(SID, I, G, V) \). This step transforms scenarios from the simulator output format to a database input format, such as comma-separated values (CSV) that the database can load.

4.3 Data Transformation and Load of Observed Data

After a disaster occurs, “Data transformation and load of observed data” involves storing observed data sent from a sensor in the database based on the observed data schema, i.e., \( R_s(OID, I, G, V) \). This step transforms observed data from the sensor output format to a database input format, such as CSV, that the database can load.

4.4 Extraction of Scenarios Similar to Observed Data

Based on an extraction condition, “Extraction of scenarios similar to observed data” involves outputting scenarios similar to observed data by comparing them with scenarios and observed data stored in the database.
Before applying simulation data composition

| Observed data | Scenario 1 | Scenario 2 | ... | Scenario N | Estimated result
|
| --- | --- | --- | --- | --- | ---
| **Database** | | | | | |

After applying simulation data composition

| Observed data | Scenario 1 | Scenario 2 | ... | Scenario N | Composition |
| --- | --- | --- | --- | --- | ---
| **Database** | | | | | **Estimated result**

Figure 1: Disaster estimation before and after applying simulation data composition.

In this step, scenarios are extracted if a pre-defined condition of extracting similar scenarios is met. This condition is met if the scenario is similar to a set of observed data. The attribute values of the scenario and observed data are compared when these time and space values intersect, i.e., \( R_p.I \) and \( R_p.I \) intersect and \( R_p.G \) and \( R_p.G \) intersect.

The processing time of checking the intersection between \( R_p.I \) and \( R_p.I \) and between \( R_p.G \) and \( R_p.G \) is considered to be long because the number of \( R_p \) records is large. To reduce the processing time of checking the intersection, a spatio-temporal similarity search method is adopted [6]. This method can be implemented on top of an existing RDBMS, which supports high-performance and reliable processing, even if a large-scale natural disaster occurs. There are currently many spatio-temporal indices [14, 16]. On the basis of a B*-tree method [10], which is an effective spatio-temporal index for moving objects, the proposed method indexes these spatio-temporal partition numbers using a one dimensional indexing method such as B*-tree, which has been implemented in most existing RDBMSs. The proposed method efficiently obtains a characteristic value of a time-series grid data item and an observed value of an observed data item under the condition in which both the time intervals and geometries of the time-series grid data item and observed data item intersect.

4.5 Composition of Simulation Data

Based on composition logic, “Composition of simulation data” involves estimating the disaster coverage from scenarios similar to observed data.

When a disaster occurs, this process creates a scenario based on pre-defined composition logic. This composition logic defines how to aggregate attribute values of multiple scenarios that hold the same spatial and temporal values. Examples of aggregation are the maximum, minimum, and average of multiple attribute values. The composition logic is determined based on the application.

5. PERFORMANCE EVALUATIONS

5.1 Performance Environment

In this evaluation, we assume damage due to an earthquake occurring below the Tokyo metropolitan region and estimation of the spread of fire caused by the earthquake. The criteria are processing time and accuracy of the proposed method. We assume that the system shows an estimated result within 30 minutes after the earthquake occurs and updates the estimated result every 30 minutes. In this situation, the performance requirement of processing the estimation is within 10 minutes, which is considered to include the processing time for extracting scenarios similar to observed data and that for composing simulation data. Therefore, we verified that the processing times of the proposed method are within 10 minutes in our assumed disaster. Moreover, we showed the accuracy of the proposed method as reference information.

The assumed disaster in this evaluation is based on reports on damage estimation caused by an earthquake occurring below the Tokyo metropolitan region, published by the Central Disaster Management Council, Cabinet Office, Government of Japan, and Tokyo Metropolitan Government. We assume a fire spreads throughout Tokyo and its surrounding areas when a large-scale earthquake in the South Kanto area (around Tokyo) occurs. In [18], we explained how to create this assumed situation by using some kinds of simulations.

Table 1 shows the disaster patterns in these experiments. These disaster patterns include four patterns in terms of damage scale, disaster occurrence time, and number of disaster information items. We set the number of firepois for large and small disasters to 900 and 130 within the Tokyo Metropolitan Region, respectively. We set the disaster occurrence times in the evening and daytime to 18:00 and 13:00, respectively. We set the large and small numbers of disaster information items to 100,000 and 8,000 per 6 hours, respectively. As an example of sending disaster information...
Before disaster occurs

![Diagram](image_url)

After disaster occurs

![Diagram](image_url)

Table 1: Disaster patterns.

<table>
<thead>
<tr>
<th>No.</th>
<th>Damage scale</th>
<th>Disaster occurrence time</th>
<th>Number of disaster info. items</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Large</td>
<td>Evening</td>
<td>Large</td>
</tr>
<tr>
<td>2</td>
<td>Small</td>
<td>Evening</td>
<td>Large</td>
</tr>
<tr>
<td>3</td>
<td>Large</td>
<td>Daytime</td>
<td>Large</td>
</tr>
<tr>
<td>4</td>
<td>Large</td>
<td>Evening</td>
<td>Small</td>
</tr>
</tbody>
</table>

items, disaster-related organizations or residents will be considered to witness the spread of fire and send the disaster information item by using a disaster prevention application on smartphones. The wind speed (8 [m/sec]) and direction (southern exposure) are constant throughout the area. In a real environment, fires may occur in some clock skew and the wind speed and direction may differ in each area. We simplified the model for this evaluation.

We created scenarios (simulated spreading fire coverage data) as follows. Many fire points were set to areas in which a risk of fire is high. The number of fire points was 6,833. The wind speed and direction were 8 [m/sec] and southern exposure. From these settings, we set a fire spread limit distance and a fire spread velocity based on a general fire spread model and calculated a time-series fire spreading coverage. From the calculated results, we created time-series grid data whose time sampling was 10 minutes, time duration was 24 hours, and whose cell was about 100 [m] × 100 [m] as scenarios. The cell held an attribute value that shows the number of burning buildings. In this setting, the number of records in all scenarios was about 15.1 million.

The extraction condition for scenarios similar to observed data is that a scenario extracts if more than two disaster information items, which are sent within 6 hours since the earthquake occurs, are obtained in the spatial cell where the number of burning buildings is at least one. The composition logic for composing simulation data is that if multiple scenarios have attribute values (the numbers of burning buildings) corresponding to a same spatial and temporal values, the attribute corresponding to the spatial and temporal value is the maximum of these attribute values. This is because the proposed method does not estimate lower than the real value. Figure 3 shows an example of fire spreading coverage estimated by the proposed method. In this figure, the background map shows a map around Tokyo. The red cells show the fire spreading coverage estimated by the proposed method in case of Pattern 1 shown in Table 1 after 6 hours since the earthquake occurred.

The proposed method was implemented on a system con-
sitting of a database server and a storage unit. The database server was connected to the storage unit by 8 Gbps four-fiber cables. The database server had four CPUs (2.4GHz × 10 cores) and 384GB RAM. An RDBMS was installed in the database server. The storage unit had 21 × RAID5 (4D+1P) arrays that consist of 105 × 10,000 [rpm] SAS hard disk drives (1.2TB). The time-series grid data and observed data were stored in the storage unit.

5.2 Results of Processing Time

In this subsection, we verify that the processing times of the proposed method are within 10 minutes in our assumed disaster.

Figures 4, 5, 6, and 7 show the results of the processing time to estimate the spread of fire in Patterns 1, 2, 3, and 4, respectively. In each figure, the horizontal axis shows the elapsed time since the large-scale earthquake occurred. The left vertical axis shows the processing times to estimate the spread of the fire. The stacked bar graph corresponds to the left vertical axis and includes the processing time of extracting scenarios similar to observed data (disaster information items) and that of composing simulation data shown in dark gray and light gray, respectively. The right axis shows the number of extracted scenarios similar to observed data. The polygonal line corresponds to the right vertical axis.

Figure 4 shows that the processing time to estimate the spread of fire was almost longer when the elapsed time since the large-scale earthquake occurred became longer. This is because the number of extracted scenarios similar to observed data became larger due to the number of burning buildings and that of disaster information items becoming larger. The processing time to estimate the spread of fire was at most about 430 seconds (when the elapsed time was 6 hours), which is within 10 minutes, which is practical. The processing time to extract scenarios similar to observed data and that to compose simulation data were at most about 50 seconds and 380 seconds, respectively (when the elapsed time was 6 hours). These results show that the processing time to estimate the spread of fire is dominated by the processing time to compose the simulation data. When the elapsed time was 6 hours, the proposed method composed 864 scenarios to estimate the spread of fire.

Figure 5 shows that the processing time to estimate the spread of fire became longer when the elapsed time since the large-scale earthquake occurred became longer. This is the same reason with regard to Figure 4. The processing time to estimate the spread of fire was at most about 430 seconds (when the elapsed time was 6 hours), which is within 10 minutes. The processing time to extract scenarios similar to observed data and that to compose simulation data were at most about 30 and 390 seconds, respectively (when the elapsed time was 6 hours). These results show that the processing time to estimate the spread of fire is dominated by the processing time to compose the simulation data. These results are the same as those in Figure 4. When the elapsed time was 6 hours, the proposed method composed 85 scenarios to estimate the spread of fire.

Figure 6 shows that the processing time to estimate the spread of fire became longer when the elapsed time since the large-scale earthquake occurred became longer. This is the same reason with regard to Figure 4. The processing time to estimate the spread of fire was at most about 430 seconds (when the elapsed time was 6 hours), which is within 10 minutes. The processing time to extract scenarios similar to observed data and that to compose simulation data were at most about 60 and 390 seconds, respectively (when the elapsed time was 6 hours). These results show that the processing time to estimate the spread of fire is dominated by the processing time to compose the simulation data. These results are the same as those in Figure 4. When the elapsed time was 6 hours, the proposed method composed 1,117 scenarios to estimate the spread of fire.

Figure 7 shows that the processing time to estimate the spread of fire became longer when the elapsed time since the large-scale earthquake occurred became longer. This is the same reason with regard to Figure 4. The processing time to estimate the spread of fire was at most about 420 seconds (when the elapsed time was 6 hours), which is within 10 minutes. The processing time to extract scenarios similar to observed data and that to compose simulation data were at most about 20 and 400 seconds, respectively (when the elapsed time was 6 hours). These results show that the processing time to estimate the spread of fire is dominated by the processing time to compose the simulation data. These results are the same as those in Figure 4. When the elapsed time was 6 hours, the proposed method composed 324 scenarios to estimate the spread of fire.

Figures 4, 5, 6, and 7 show that the processing times of the proposed method are within 10 minutes. Therefore, the proposed method is practical from the view point of processing time.

5.3 Results of Accuracy

In this subsection, we show the accuracy of the proposed method as reference information.

Figures 8 and 9 show the results of the recall and precision of the estimated spread of fire throughout the 23 wards in central Tokyo 6 hours after the large-scale earthquake occurred. We argue that the number of disaster information items mainly affects the accuracy of the estimated fire spread. Therefore, we compared the accuracy of the estimated fire spread in Patterns 1 and 4. Figure 8 shows the recall of the estimated fire spread. This recall is defined by the ratio of the number of correct burning grid data items included in an estimated result to the number of burning grid data items included in true data. Figure 9 shows the
precision of the estimated spread of fire. This precision is defined by the ratio of the number of correct burning grid data items included in an estimated result to the number of estimated burning grid data items.

Figure 8 shows that the estimated results in Pattern 1 suggest higher recall than those in Pattern 4. This is because the disaster information in Pattern 1 was distributed widely and the estimated fire-spread distribution became wider. However, Figure 9 shows that the estimated results in Pattern 1 suggest lower precision than those in Pattern 4. These results show that the number of imprecise burning grid data items in Pattern 1 became larger. Future consideration is to reduce the number of imprecise burning grid data items.

6. CONCLUSION
This paper presented a combination method of simulation data in order to apply the STSim method for estimating disasters occurring at multiple locations. This proposed method stores scenarios, each of which represents a disaster occurring at a single location, to a database; thus, reducing the number of scenarios. After a disaster occurs, it extracts and composes scenarios similar to observed data, resulting in efficient disaster estimation in any situation. We conducted performance evaluations under the assumption of an earthquake occurring below the Tokyo metropolitan region and estimation of the spread of fire in the initial response. These results of the processing time for estimating the spread of fire showed that the processing time of the proposed method is within 10 minutes, which is practical.

Our future work includes how to provide estimated disaster information to disaster-related organizations to support their decision making.

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