Integrating Physical Prediction Methods and AI-based Satellite Data Analysis Methods in Earthquake Damage Estimation

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Abstract

In order to estimate the damage distribution immediately after an earthquake, both physical prediction methods and data-driven methods that analyze sensing data obtained from satellites are used. However, the former has the problem of prediction accuracy, while the latter has the problem of difficulty in detecting detailed damage patterns such as partial destruction. Therefore, we present a method that improves the detection accuracy of detailed damage distribution of structures such as total and partial collapse by integrating both methods. As an integration scheme of the two methods, a data assimilation method based on Bayes’ theorem is adopted in this study. We proposed a method to update the damage probability of each structure obtained from physical simulations by conditioning it on the observed data obtained from satellite image analysis, and verified its effectiveness.

Keywords: earthquake damage detection, deep learning, physical simulation, data assimilation

1. Introduction

It is essential to collect information on the damage distribution in the affected area for the initial response after the disaster in a major earthquake. Among the various information collection methods, analysis of images taken from artificial satellites is considered a promising method [1], and technology development for practical application is underway [2], [3]. In particular, the use of deep learning techniques which has been greatly developed in recent years has dramatically improved the performance of damage detection from images [4], [5].

However, since satellite images are taken from directly above, they do not have information on partial destruction, such as damage to the sides of structures, and it is difficult in principle to detect such detailed damage from the images. Actually, it has been pointed out that damage detection using machine learning has reached its accuracy limit due to the lack of such essential information in satellite images [6]. Therefore, different information sources and approaches are needed to understand the detailed damage patterns of structures such as half-destruction and partial destruction.

On the other hand, physical simulation is another method for assessing earthquake damage distribution [7]–[9]. Although the accuracy of the simulation is not yet high enough to match the actual situation, it can predict detailed damage patterns such as half-destruction and is expected to be a method that can compensate for the shortcomings of satellite images.

Therefore in this study, we propose a scheme that integrates damage estimation methods from satellite images and physical damage prediction methods to break through the limitations of damage assessment from satellite sensing images and improve the accuracy of damage detection, including detailed damage patterns. As a concrete means of integration, this paper adopts a data assimilation method based on Bayes’ theorem [10], and mathematical formulations are given.

This paper is organized as follows: Chapter 2 formulates the proposed method. Chapter 3 describes the numerical experiments to verify the effectiveness of the proposed method. Chapter 4 summarizes and discusses the results of the numerical experiments. Finally, chapter 5 summarizes this paper and discusses future issues.

2. Proposed Method

This study adopts a data assimilation method based on Bayes’ theorem as a scheme to integrate a damage estimation from satellite images with a physical simulation.

In the data assimilation method, the prior probability of a physical quantity obtained from a physical simulation is updated to the posterior probability using the likelihood of the observed value. Let the prior and posterior probabilities of a physical quantity \(x\) be \(p(x)\) and \(p(x|D)\) respectively, and the probability of the observed value \(D\) and the likelihood under the physical quantity \(x\) be \(p(D)\) and \(p(D|x)\), then the following equation is derived from Bayes’ theorem.

\[
p(x|D) = \frac{p(D|x)p(x)}{p(D)} \tag{1}
\]

The data assimilation methods used in many applications can be roughly classified into two types: variational methods, such as the 4D variational method, and sequential methods, such as particle filters. In this study, we formulate the data assimilation method for the damage probability of individual structures as follows.

Let \(D = \{D_i|i = 1,...,n\}\) be the set of structure states determined from satellite images, and \(X = \{x_i|i = 1,...,m\}\) be the set of structure states obtained from numerical simulations. Here, \(D\) is assumed to contain only the rough structure states obtained from satellite images, such as only 2 classes of total destruction or no damage, while \(X\) is assumed to contain more detailed states, such as partial destruction or partial damage. In case the true state of the structure is \(x_i\), we define the likelihood that the state of the structure is inferred to be \(D_f\) from the satellite image analysis as \(p(D_f|x_i)\), and the probability that the state of the structure is determined to be \(x_i\) from the physics simulation as \(p(x_i)\). Then, the following equation is obtained from Eq. (1).
According to the above equation, the damage state probability $p(x_i)$ of the structure obtained from the physical simulation is updated based on the damage estimation result $D_j$ from the satellite observation. Adopting this method is expected that both the certainty of damage detection provided by satellite image analysis and the detailed damage estimation provided by physical simulation can be achieved.

3. Numerical Study

In order to verify the proposed method described above, numerical experiments were conducted under the following conditions.

3.1. Target Data

The data used in this study was from an exhaustive survey in Mashiki-town in Kumamoto Prefecture, Japan, which was severely damaged by the Kumamoto Earthquake in 2016. This data consists of the location, age, structure type, and damage grade of 2340 buildings. In this study, we set three structural states which would be estimated by physical simulation: no damage ($x_0$), partially damaged or more ($x_1$), and total collapse ($x_2$), which was a set of structural states $X = \{x_0, x_1, x_2\}$. The correspondence between these structural states and original damage grades were shown in Tab. 1.

Fig. 1 shows the distribution of structural state $x_1$ & $x_2$ in the target area. Note that the locations of $x_2$ are overlapped with $x_1$, because $x_1$ is defined as "partially damaged or more" and therefore includes total collapse.

3.2. Physical Simulation

As a physical simulation of earthquake damage, the fragility curve method is used to estimate the probability of damage state of a structure based on the maximum seismic velocity PGV and the structure attributes. The calculation of the damage probability by the fragility curve is expressed as follows.

$$
p(x_i|D_j) = \frac{p(D_j|x_i)p(x_i)}{p(D_j)} = \frac{p(D_j|x_i)p(x_i)}{\sum_{k=1}^{n} p(D_j|x_k)p(x_k)}
$$

(2)

Here $x_i$ indicates the structure state described above, $y$ stands for the age of the structure, $s$ stands for the structure type, and $\Phi$ is the cumulative probability distribution function of the standard normal distribution. The values of the parameters $\lambda|y,s$ and $\xi|y,s$ were given following Miyakoshi et al [11].

3.3. Satellite imagery analysis

We used the method of Miyamoto et al. [6] to estimate earthquake damage based on satellite imagery analysis. The outline of the method is as follows.

The pairs of satellite images captured before and after the earthquake, on January 16, 2016, and April 20, 2016, respectively, at optical satellite Pleiades were used for the analysis target. The resolution of the images was 0.5 m/pixel. Small images of each structure were extracted from the whole imagery, and each fragment was then resized to $20 \times 20$ pixels to unify the image sizes and used as the input data.

As a damage classifier of each building, the multimodal deep learning model whose input is a pair of images, as well as structural attributes, was adopted. The model provides a binary classification of whether the structure corresponding...
to the input data is no damage \((D_0)\) or totally destroyed \((D_1)\). Fig. 2 shows the classified results by the model.

The relationship between the structure state \(x_i\) and the model’s estimation result \(D_i\) for the target data is shown in the Tab 2. From this result, the likelihood of \(D_i\) was calculated as shown in the Tab. 3 and used for the calculation in Eq. (2).

### 4. Results and Discussion

Fig. 3 shows the distribution of prior probabilities of structure states \(x_1\) and \(x_2\) obtained only from the physical simulation. It can be pointed out that the results in Fig. 3 tend to overestimate the damage as a whole when compared with the ground truth in Fig. 1. Especially, the probability of being partially destroyed or more \((x_1)\), shown in Fig. 3(a), is estimated to be high over the entire area, with no regional differences, which is far from the actual situation.

In contrast, the posterior probability distribution obtained from the proposed method is shown in Fig. 4. Comparing Fig. 3(a) with Fig. 4(a), the posterior probability distribution changes significantly, indicating that the conditioning by the satellite image analysis results in Fig. 2 is working well. The comparison with Fig. 1(a) also shows that the posterior distribution is more consistent with the actual damage distribution. In Fig. 4(b), the distribution of the structures with a high probability of total collapse shown in the red circles has also changed significantly, which is closer to the actual damage distribution in Fig. 1, indicating that the correction of the simulation results by the proposed method works effectively.

### 5. Conclusion

In this paper, we proposed a scheme to integrate the two methods in order to utilize both the certainty of satellite image analysis and the possibility of estimating the detailed damage form of physical simulation in complementary ways. As a concrete integration scheme, we adopted the data assimilation method and formulated it so that satellite image analysis results update the damage probability obtained from physical simulation. The accuracy of the updated damage probability was discussed qualitatively based on the analysis results in one region. In the future, it is necessary to discuss the effectiveness of the proposed method in detail through quantitative verification in various regions.

In addition, the integration of physical simulation and AI analysis methods aimed at in this paper can take various forms. For example, in contrast to this paper, the image analysis results can be corrected by physical simulation, or the information about input seismic motion, which is highly uncertain in physical simulation, can be corrected. Therefore, we would like to compare these various methods and study the best integration method in the future.

### References


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**Figure 2.** Classified results of structural damage by satellite image analysis

**Table 2.** Relationship between the structure state \(x_i\) and the model’s estimation result \(D_i\)

<table>
<thead>
<tr>
<th>(x_i)</th>
<th>(D_0)</th>
<th>(D_1)</th>
<th>total no.</th>
</tr>
</thead>
<tbody>
<tr>
<td>(x_0)</td>
<td>1444</td>
<td>50</td>
<td>1494</td>
</tr>
<tr>
<td>(x_1)</td>
<td>641</td>
<td>205</td>
<td>846</td>
</tr>
<tr>
<td>(x_2)</td>
<td>24</td>
<td>50</td>
<td>74</td>
</tr>
</tbody>
</table>

**Table 3.** Likelihood of \(D_i\) under the condition \(x_j\)

\[
\begin{align*}
\text{Pr}(D_0|x_0) & = \frac{1444}{1494} = 0.97 \\
\text{Pr}(D_1|x_0) & = \frac{50}{1494} = 0.03 \\
\text{Pr}(D_0|x_1) & = \frac{641}{846} = 0.76 \\
\text{Pr}(D_1|x_1) & = \frac{205}{846} = 0.24 \\
\text{Pr}(D_0|x_2) & = \frac{24}{74} = 0.32 \\
\text{Pr}(D_1|x_2) & = \frac{50}{74} = 0.68
\end{align*}
\]
Figure 3. Distribution of prior probabilities for $x_1$ and $x_2$: results obtained from physical simulation

Figure 4. Distribution of posterior probabilities for $x_1$ and $x_2$: results obtained from data assimilation scheme


