Visualization of Predicted Ground Vibration Induced by Blasting in Urban Quarry Site Utilizing Web-GIS

Yoshio Moriyama[a]*, Youhei Kawamura[a], Hyongdoo Jang[b]

a. Akita University, Akita, Japan
b. Curtin University, Kalgoorlie, Australia

ABSTRACT: Blasting is routinely carried out at various quarries. When blasting is done in an urban area, the ground vibration induced by the operation may affect nearby residents physically and mentally. In this study, a visualization system of ground vibration induced by blasting is constructed for the purpose of reducing these adverse effects. The system consists of two phases. The first is the ground vibration prediction by using artificial intelligence, specifically an ANN (Artificial Neural Network). The second is the visualization of the predicted vibration through Web-GIS. Four prediction factors, namely MIC (Maximum Instantaneous Charge), distance, elevation difference, and direction were used and PPV (Peak Particle Velocity) was used as an index of ground vibration strength. Colored contours representing vibration intensity were generated using GIS tools based on predicted PPV. Furthermore, the contour is converted into a KMZ file and overlaid on a web-based map (Google Maps) that also displays other pertinent information about the quarry vicinity. This means that the system can be used by anyone who has an internet connection and access to a browser. The data would be available to residents, local government officers, and anyone else who wishes to use it. In addition, the ground vibration prediction data and contour maps could also be used to optimize blasting designs in advance. Through the use of this system, optimal blasting can be done, maximizing the productivity of the quarry as well as minimizing the impact on the local residences.

KEYWORDS: Visualization, Blasting, ANN, Web-GIS, PPV prediction

1 INTRODUCTION

Blasting is carried out on a daily basis at resource extraction sites. A lot of problems such as ground vibration, fly rocks and dust often occur at these site where blasting is carried out. To avoid conflicts with residents, it is wiser for urban quarry sites to pay particular attention most to these problems. Though residential houses and other structures may not be significantly affected, the ground vibrations induced by blasting can cause anxiety and/or discomfort to residents, hence the need to solve such problems. In previous researches, it has been observed that mental distress such as anxiety experienced by surrounding residents can be alleviated by providing blasting information prior to blasting activity [1]. More on such previous researches which have been done include those that specifically aimed at developing a ground vibration prediction model by using nonlinear expressions and artificial intelligence [2] – [5]. However, few researches have been conducted for the purpose of developing a system that could potentially reduce the influence on neighboring residences using prediction of ground vibration induced by blasting [6] [7].

In this research, we designed a system for visualizing ground vibration induced by blasting on an easily accessible map of the web, with emphasis to an urban quarry site. As a system construction procedure, a prediction model is generated using ANN (Artificial Neural Network), hence employing artificial intelligence (AI). The prediction model is used to predict a given area around the quarry site. To represent different ground vibration strengths, a color contour was created by employing a GIS (Geographic Information System) tool based on the predicted values. Furthermore, the color contour is visualized on the map of web area using Web-GIS. GIS and Web-GIS have often been used for land use maps such as geology, hazard maps, disaster simulation and research on dynamic management systems for resource extraction sites [8] – [12]. The proposed system design is shown in Fig. 1. By visualizing the predicted blasting induced ground vibration intensity on the web, anyone can browse the internet and access blasting information if/when desired. Therefore, there is a potential to reduce mental distress if residents around the quarry site take advantage of this system. In addition, it can be expected to be used for various things such as system monitoring by employees and use for other research by researchers.

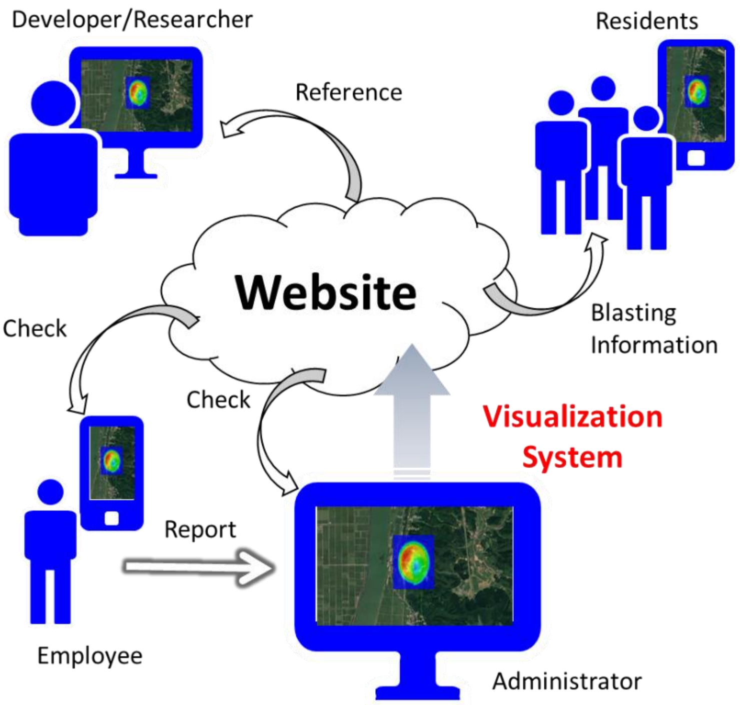

Fig. 1 System design

2 SYSTEM CONSTRUCTION

The proposed system construction procedure is shown in Fig. 2. It features a prediction and a visualization phase. In the prediction phase, ground vibration data is collected to create a prediction model of blasting induced ground vibration. The ground vibration data is obtained as voltage values (V or mV) and are ultimately converted to velocity. PPV (Peak Particle Velocity), which is a general index for evaluating the ground vibration strength is then obtained from this data conversion [13]. Based on the collected data, a prediction model is then generated using ANN. We predict PPV based on conditions such as latitude and longitude, blasting design, geographical conditions, etc., using a prediction model. In the visualization phase, we use GIS to create a color contour representing vibration intensity based on predicted PPV linked to latitude and longitude. Its use is however limited as it requires a dedicated application to employ data created by GIS. Therefore, in order to expand the displayed area, PPV contours are visualized on a website map using Web-GIS. This completes a system that anyone with a browser can access. The following text describes in detail the creation of a prediction model using ground vibration measurement and ANN; and a visualization system using Web-GIS.

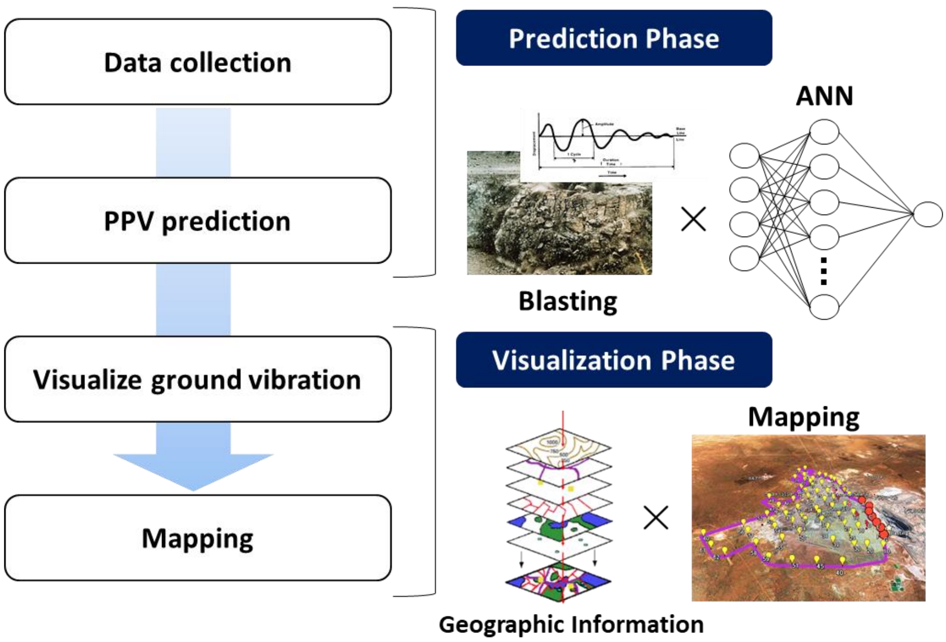

Fig. 2 System implementation procedure

2.1 Measurement of Ground Vibration and Generation of a Prediction Model Using ANN

The data collection and visualization system of ground vibration induced by blasting were implemented for the Mikurahana quarry site located in Hachirogata-town, Akita Prefecture.

The schematic diagram of the apparatus is shown in Fig. 3. Ground vibration data was collected using two types of measuring instruments, a 3-axis fine vibration detector and a 1-axis accelerometer. The ground vibration data is acquired as a voltage value (V or mV), and is converted from the voltage value to acceleration by multiplying the calibration coefficients of the 3-axis fine vibration detector. 1-axis accelerometers with different calibration coefficients are adjusted to the same calibration coefficient by using an amplifier. The ground vibration data is finally converted to velocity and PPV is obtained. Since velocity is not affected by changes in geological conditions unlike acceleration and displacement, consistency and predictability can thus be maintained even if conditions such as rock type and distance vary [14]. Each measurement time is 1.6 seconds and the sample frequency is 10 kHz. Using spreadsheet software, we are able to create a velocity-time graph from which we are able to extract PPV from.

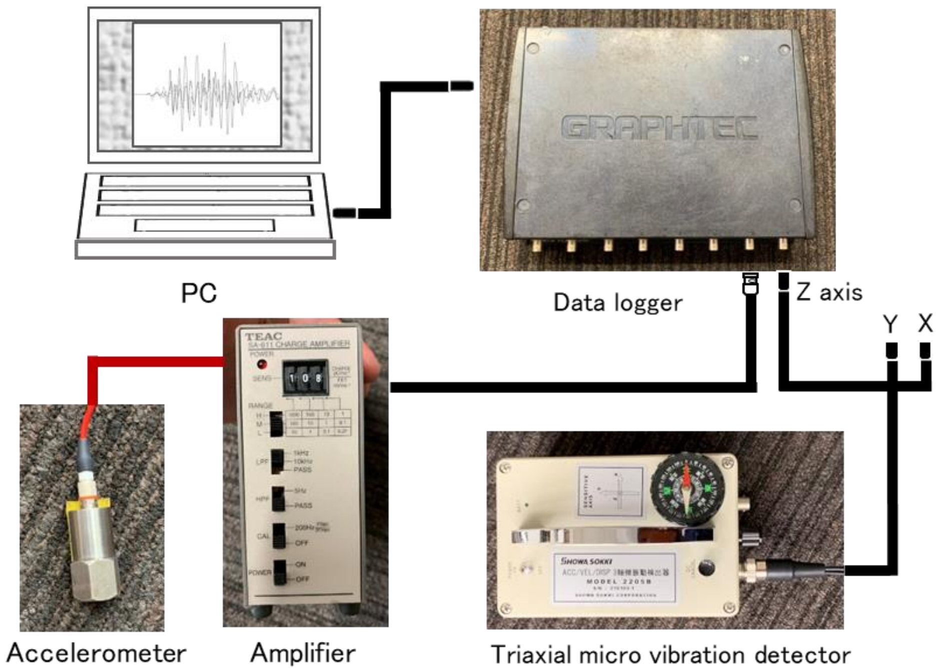

Fig. 3 Schematic diagram of measurement apparatus

MATLAB's ANN was then used to create a prediction model of ground vibration induced by blasting. As input data, 4 variables namely MIC (Maximum Instantaneous Charge), distance, direction and elevation difference were used together with PPV obtained by measurement as output data. MIC represents the amount of explosive that simultaneously explodes within 8 ms. ANN is a part of artificial intelligence that mathematically expresses the mechanism of the human brain. Specifically, ANN belongs to a class of machine learning classes and is a mechanism that can perform simulations such as classification and regression. To compare the prediction performance of the prediction model using ANN and the empirical model. The empirical model was chosen to be similar to target site minerals. The Equation 1 is shown below.

$$\mathrm{PPV}(m/s) = 0.362D^{-1.63} \quad (1)$$

Here, D = R/Q$^{1/2}$, R (m) represents the distance from the blast point to the measurem ent point, and Q (kg) represents the MIC. The prediction model using ANN was also trained with two inputs (distance and MIC). The result of comparison is shown in Ta ble 1.

Table 1 Comparison results of prediction performance

PPV (Empirical model)	PPV (ANN)	PPV (Measured value)
0.232	0.681	0.500
0.307	0.578	0.603
0.922	0.568	0.468
0.440	0.680	0.735

※ Units is (mm/s)

It can be seen that the prediction model using ANN is better, based on the Table 1. In this study, ANN was used to generate a prediction model using 64 sets of input data. This data set was divided into training, test and validation data at ratios of 80%: 10%: 10% respectively. Fig. 4 shows a system conceptual diagram of the prediction model; this simple 3-layer neural network was employed. Data is fed into the input layer, weights are then applied when proceeding into the hidden layer, and their interaction given as output results. Weights can easily be changed so as to reduce comparison errors by feeding back previously learnt output results back into the neural network. By repeating this cycle of input, prediction, comparison, and feedback, the comparison error becomes less significant. In other words, learning simply refers to the optimization of the weight.

After network training, performance evaluation of the neural network is performed using test and validation data. An example of graph representing the performance of neural network is shown in Fig. 5. Generally, the error decreases as the number of learning epochs increases, but the error in the verification data increases when there is network overfitting to the learning data. At this time, learning stops when the error increases six consecutive times. The best performance is obtained from the epoch with the smallest verification error. The training result is judged as a regression value and a mean squared error. The most desirable result from these variable is one where the regression value is closest to 1, and mean square error closest to 0. The number of hidden layer neurons was divided into cases different (4, 6, ..., 12) so as to compare the performance of the prediction model across these. The comparison results of each prediction model is shown in Table 1. From the regression rate and the mean square error, it was made evident that the prediction model with 12 artificial neurons in the hidden layer showed the best performance. The vertical axis indicates predicted PPV (mm /s) based on the input, and the horizontal axis indicates measured PPV (mm / s) corresponding to the input. In this graph, plots and approximate lines of each variable are drawn, and the correlation between predicted PPV and measured PPV is shown. The higher the best fit line on the plot, the higher the regression rate. The regression rate of each variable is 0.959 for training, 0.764 for verification, 0.876 for test data, and 0.907 for all data sets as a collective. Although one might argue that these regression rates are acceptable since they are close to 0.9, they are however lower as compared to those attained in previous studies. Reason for this low rate is attributed to the shortage of data.

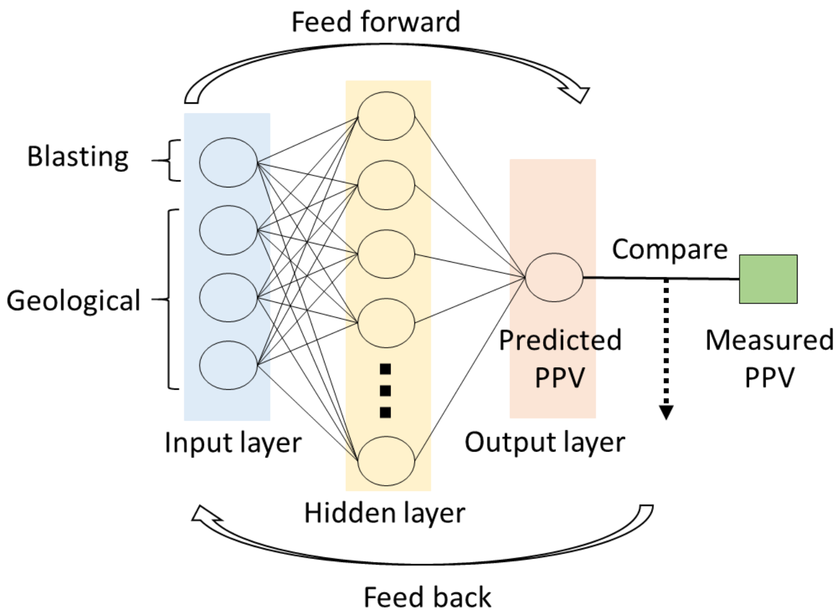

Fig. 4 Conceptual diagram of artificial neural network

Table 2 Comparison result of prediction model

Data Name	Number of Artificial Neuron	MSE	R Value
Learning Data		0.0095	0.906
Validation Data	4	0.0099	0.939
Test Data		0.0181	0.826
Learning Data		0.0058	0.954
Validation Data	6	0.0061	0.934
Test Data		0.0102	0.803
Learning Data		0.0082	0.931
Validation Data	8	0.0256	0.92
Test Data		0.0471	0.783
Learning Data	10	0.006	0.95
Validation Data		0.0087	0.768

Test Data		**0.0142**	**0.867**
Learning Data		**0.0042**	**0.959**
Validation Data	**12**	**0.0221**	**0.764**
Test Data		**0.0516**	**0.876**

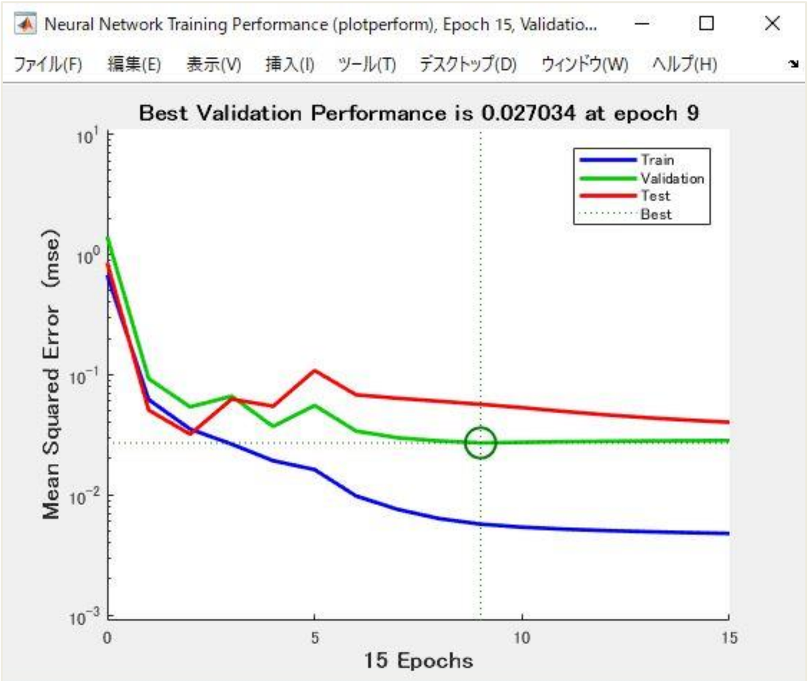

Fig. 5 Performance graph of neural network

2.2 Predicted Vibration Visualization System Using Web-GIS Technology

First, using a prediction model, PPV prediction of 10,000 points around the Mikurahana quarry site is performed. The point (latitude 39.9863, longitude 140.0788) at the lowermost layer of the Mikurahana quarry site was set as the blast point. As the prediction conditions, MIC and elevation differences were kept constant because the standard deviation of learning data was small, and the distance and direction used each value. The prediction results were saved in a CSV (Comma-Separated Values) file format along with coordinate information of each point. There were negative values in the prediction results, and the prediction accuracy in the southeast direction was poor especially around the center point. Taking into consideration the negative values, it is possible that they are at points where the ground vibration does not reach at all. In the future, it is necessary to improve the data shortage, but since there are neither any buildings nor people living in the mountainous area, this is a region that does not need to be considered at this time.

Next, a color contour representing the vibration intensity is created by using GIS, based on the predicted data. The basic map information around the Mikurahana quarry site used in GIS was retrieved from the Geographical Survey Institute website. In Fig. 6, the imported predicted values are shown as markers. The markers are divided into five colors because the data was divided into five CSV files. Color contours were created by converting the marker information, which is vector data, into raster data. An example of the created PPV color contour is shown in Fig. 7. The color of the contour indicates the relative strength of the vibration, from blue (smaller) to red (larger). As described above, there is a range in which the color distribution of the color contour is inaccurate because the prediction performance of the prediction model is not high. In order to solve this problem, it is necessary to increase the amount of data and review the prediction conditions. Here, the negative value is corrected as 0 because it reflects the magnitude of the numerical value regardless of the sign. At this stage, the study was able to visualize the predicted vibration of ground vibration induced by blasting. However, its use is limited as it requires a dedicated application to employ data created by GIS. Therefore, it is beneficial to build a system that anyone can use by overlaying color contours visualized on the web-based maps.

Predicted vibration is visualized on the map of the web using Web-GIS. The basic map of the immediate locale is acquired from Google Maps. Color contours created via GIS need to be converted to KML (Keyhole Markup Language) file format so that they can be used easily in HTML (Hyper Text Markup Language). The KML file is one of the markup languages and it is used to display geographic data in Google maps and Google Earth. Therefore, the contour which is raster data is converted to TIFF (Tagged Image File Format), and is displayed on Google Earth. The color contour displayed in Google Earth is then converted to the KMZ file format. The KMZ file is composed of a main KML file and sometimes one or more support files, which are packaged as a zip file. A folder named KMZ was created in the same hierarchy as the index.html file used to edit the web area, and the KMZ file was saved in that folder. Finally, a program was written to call the basic map from Google map in HTML and a program to read KMZ file from KMZ folder in index.html file. As a result, the color contour can be overlaid on the basic map called in the web area, and a predicted vibration visualization system of ground vibration caused by blasting is completed. An example of a predicted vibration visualization system completed is shown in Fig. 8.

The shape of the color contour was deformed when the color contour was overlaid on the web. It is thought that the cause of this is that the spatial reference system of GIS and Google map is different. As shown in Fig. 8, since the color contour is linked to the latitude and longitude, the shape changes in accordance with the map enlargement operation. By using this system, anyone can obtain predicted vibration information of ground vibration induced by blasting.

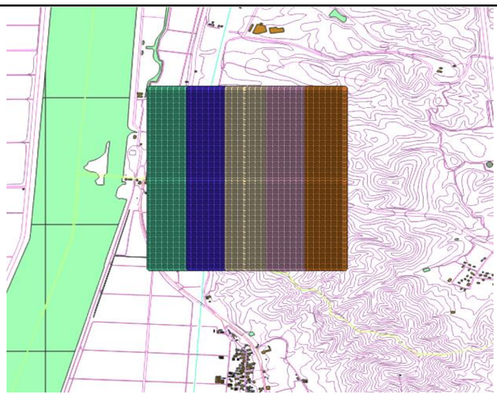

Fig. 8　Markers based on predicted PPV

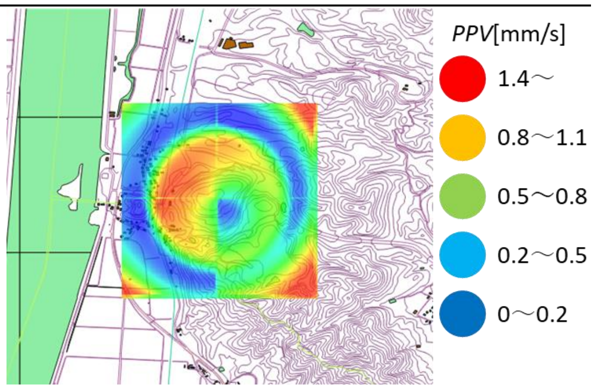

Figure 7 Contour of PPV

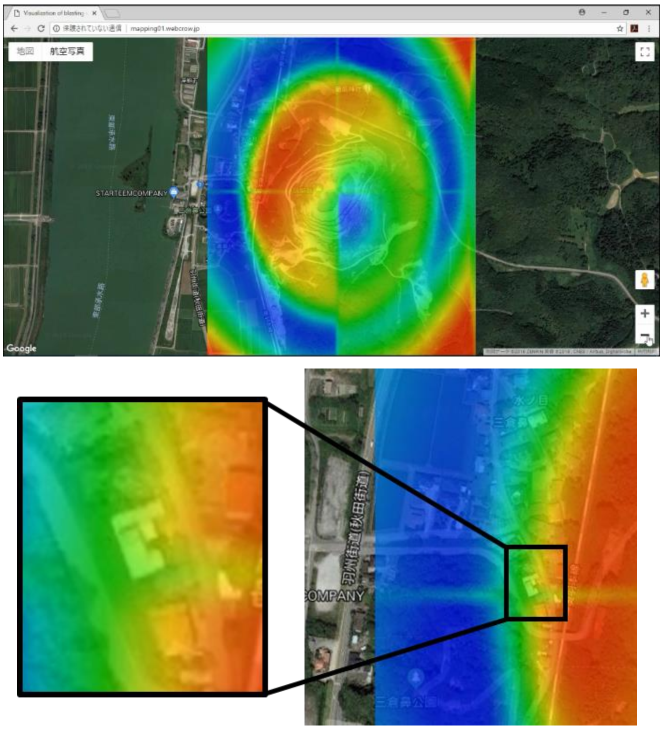

Fig. 6　Predictive vibration visualization system using Web-GIS

3　CONCLUSIONS

At resource extraction sites, blasting is carried out as usual. There is a possibility that residents in urban area be affected mentally and physically by ground vibration induced by blasting. In this study, a system that could reduce the adverse effects of ground vibration induced by blasting to nearby residents was constructed. Anyone with a browser can easily view ground vibration information in their location overlaid on a map, operating similarly to Google Maps. Additionally, since the information on the ground vibration induced by blasting can be known in advance, there is a possibility that the mental stress of nearby residents can be reduced prior to blasting. Also, employees who work at the quarry site can confirm the predicted ground vibration strength and correct blasting design. As a result, optimal blasting can be performed with the maximum crushing efficiency and the minimum range of ground vibration. Furthermore, the ground vibration information from this system is open to public and can be used by researchers in other fields of study.

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