Automatic Breaking System of Large Rocks by use of Force Sensors

Hiroshi TAKAHASHI and Takashi MONDEN
Dept. of Geoscience and Technology, Graduate School of Engineering,

Abstract:

The automation of breaking task of large rocks consists of 1) automatic detection of large rocks, 2) automatic control to make the breaker tip move to the surface of the large rocks, and 3) carrying out the breaking task. In the previous study, the image processing procedures to detect the large rocks and to measure the three dimensional information of large rock position were investigated. In this study, the algorithm to judge the breaking is proposed by use of force sensors.

Through the experiments of rock breaking, it was found that large compressive or tensile strain were obtained at the moment of rock breaking. The utilization of the neural network was proposed in this study to construct the algorithm to judge the rock breaking. It was confirmed that this algorithm works well from the experiments.

1. INTRODUCTION

Most of the limestone mines in Japan utilize the vertical shaft to deliver the rocks into the crusher as shown in Figure 1. That is, rocks are usually carried by a dump truck from the working face to the vertical shaft, and they are dropped off into the vertical shaft. Then, they are crushed by the crusher. However, if the large rocks are delivered into the crusher, they will damage the crusher. Therefore, a grizzly bar is usually set above the crusher to catch the large rocks. Then, the large rocks on the grizzly bar are broken by the hydraulic breaker. However, the working environment in the breaking room is not so good for workers because of much dust and machine vibration. Some mines utilize the remote controlled breaking system. This system enables the operators to work in a clean environment. But, it requires the skill to operate the hydraulic breaker and long work to avoid the blockage. Therefore, recently the automation of breaking system for large rocks has been receiving considerable attention [1-4].

In order to automate the detection and breaking of large rocks, an intelligent working robot is necessary. This robot is required to have an ability to recognize the working environment and to perform the task autonomously because the position of the large rock is not always constant and the shape of the large rock is not uniform.

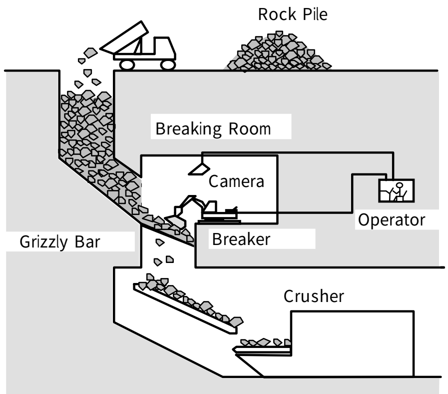

Fig.1 Schematic of rock breaking system used in the limestone mines in Japan

Figure 2 shows the automatic detection and breaking system of large rocks proposed in this study. This system consists of following three procedures.

1)Automatic detection of large rocks by image processing
2)Measurement of the large rock position and movement of the breaker tip to the surface of the large rock
3)Carrying out the breaking task by hitting the large rocks

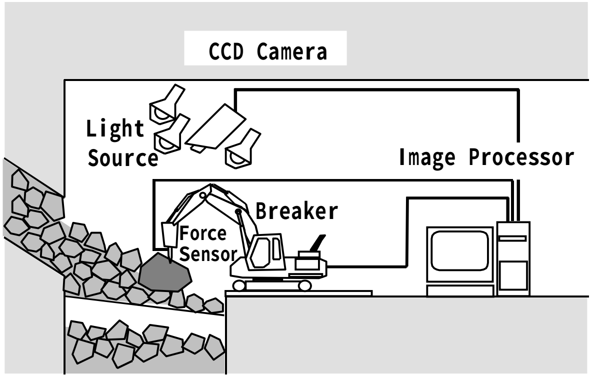

Fig.2 Automatic breaking system proposed in this study

The authors have already investigated the image processing system to detect the large rocks and measuring system of large rock position by using the CCD camera and laser spot. After the large rock is broken in the task 3), the machine has to be stopped immediately because continuing the hit without the large rock is very bad for the machine. That is, in order to realize the automation of task 3), the algorithm to recognize the breaking of the large rock is necessary.

Therefore, the objective of this study is to propose the system to judge the breaking of large rocks by use of force sensors.

2. EEPERIMENTAL CONSIDERATION ON ROCK BREAKING

2.1 Rock Breaking by Use of Actual Breaker

The rock breaking experiment was carried out at the crushed rock quarry (Hayama Saiseki Co.LTD) in Shiroishi city, Miyagi Pref., Japan. In this study, the strain gauge was used as a force sensor. Two strain gauges were attached on the side of the breaker tip, which is called "chisel". Figure 3 shows the "chisel" of the breaker with strain gauges.

As shown in Figure 4, the hydraulic hammer hits the chisel and this hitting force is transmitted to the rock through the chisel. Therefore, the strain gauges attached on the side of the chisel can measure the strain of the chisel.

Figure 5 shows the measuring system. The signals from the strain gauges were transmitted through a bridge box, a strain meter and an A/D converter to the personal computer. The sampling frequency was determined at 500 Hz with considering that the rock is usually broken quickly.

Fig.3 Chisel with strain gauges

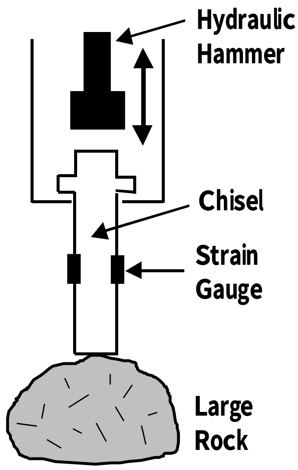

Fig.4 Structure of the hydraulic breaker

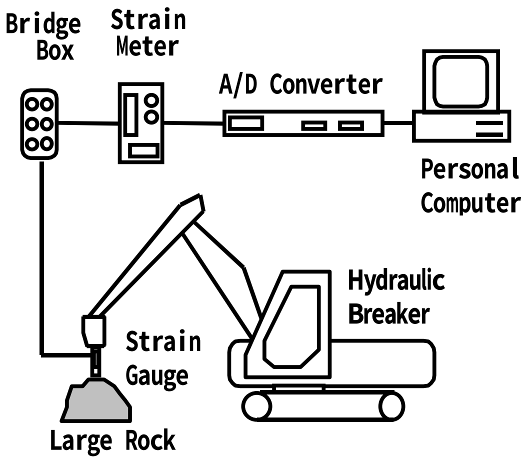

Fig.5 Measuring system by use of actual hydraulic breaker

Rock sample used in this experiment was andesite. The physical properties of rock sample are listed in Table 1. The first, large rocks were selected from the crushed rocks produced by blasting and the breaker tip was made to move to the surface of the large rock. At this time, the strain was set zero and then the hitting was given to the large rock through the chisel.

Table 1 Physical properties of rock sample

Rock	Density [kg/m^3]	Uniaxial Compres-Sive Strength [MPa]	Young's Modulus [GPa]	Poisson's Ratio [－]
Shiroishi Andesite	2690	181.3	10.59	0.339
Shirakawa Welded Tuff	2057	34.2	3.57	0.167
Mortar	2258	98.9	30.31	0.233
Towada Green Tuff	2190	40.6	13.44	0.201

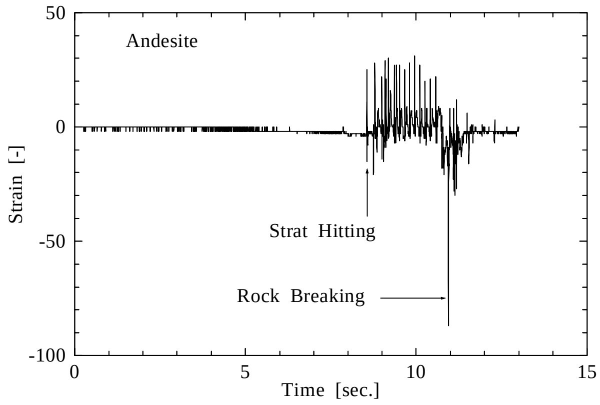

Fig.6 An example of the measured strain data (Andesite)

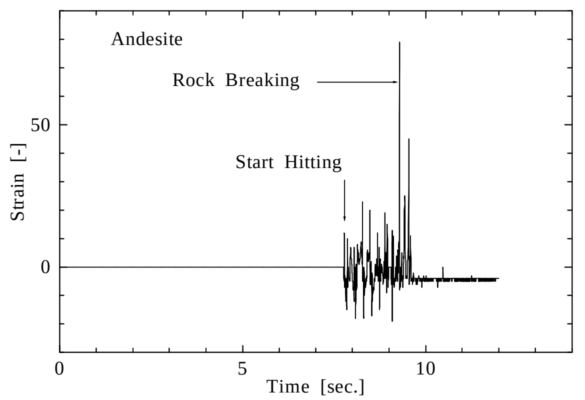

Fig.7 An example of the measured strain data (Andesite)

Figures 6 and 7 show the examples of the measured strain data while hitting the large rock by the hydraulic breaker. After the hitting starts, the wave with large amplitude is observed. In Figure 6, a large negative strain was obtained when the rock was broken. When the large rock is broken, as the chisel moves downward rapidly, "the tensile strain" is usually observed. In a result, a large negative strain is obtained as shown in Figure 6. But, a large positive strain was obtained when the large rock was broken as shown in Figure 7. That is, sometimes the chisel hits the rock that is located under the large rock or the surface of the ground hardly when the large rock is broken. In this case, "the compression strain" is obtained as shown in Figure 7. Therefore, if the large tensile or compression strain is obtained, it can be judged that the large rock is broken.

2.2 Rock Breaking by Use of Small Hydraulic Breaker Model

In order to collect the data through the experiments by using some other rocks, a laboratory experiments were carried out by use of small hydraulic breaker model shown in Figure 8. As shown in this figure, the hitting was provided by the hydraulic cylinder, which was controlled by the flow rate through an electromagnetic flow-direction control valve. In this experiment, the cutting rod for the crawler drill was used as "chisel", and two strain gauges were attached on the side of the rod. The first, the rod was set on the rock and the rod was hit by the hydraulic cylinder. The measuring system is the same as the one mentioned above. Since the hard rock such as granite was difficult to break because of the limitation of the experimental apparatus, the rock samples used in this experiment were Shirakawa welded tuff, mortar and Green tuff. The physical properties are listed in Table 1.

The hitting frequency of the actual hydraulic breaker is about 15Hz, but the hitting frequency of the small hydraulic breaker model is about 3-4Hz.

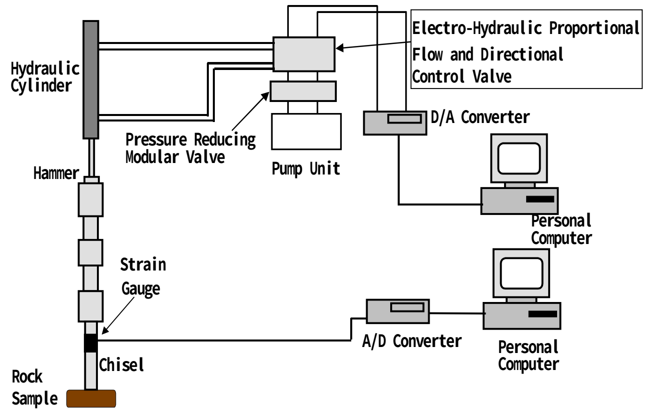

Fig.8 Schematic diagram of the experimental apparatus (small model)

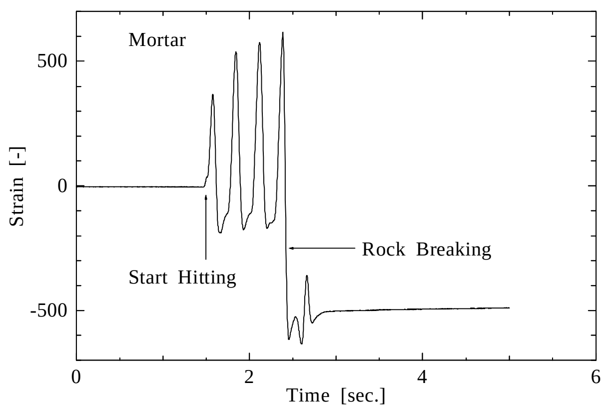

Fig.9 An example of the measured strain data (Mortar)

Figure 9 shows an example of the measured data while hitting the large rock by the breaker model. In this figure, a large tensile strain was obtained when the rock was broken. This result was the same as the one shown in Figure 6.

3. Algorithm to Judge the Rock Breaking by Neural Network

3.1 Detection of the feature

It was found through the experiments that the large tensile or compressive strain was obtained when the large rock was broken. Therefore, if the large tensile or compressive strain is obtained, it can be considered that the large rock is broken. This judgment system is regarded as the pattern recognition[5]. Usually, pattern recognition consists of two stages, that is, 1)detection of the feature and 2)classification.

By the way, the hammer hits the chisel and this hitting force is transmitted to the rock. Therefore, the peak was observed in the measured strain wave at each hitting as shown in Figure 10. So, the maximum and minimum value in the time interval, Δt which was calculated from the hitting frequency were used as the feature points. Furthermore, S_{max} and S_{min} were normalized by the amplitude while hitting in order to avoid the difference of machine ability. This amplitude was measured by hitting the hard ground.

$$T_{max} = S_{max} / A \qquad (1)$$

$$T_{min} = S_{min} / A \qquad (2)$$

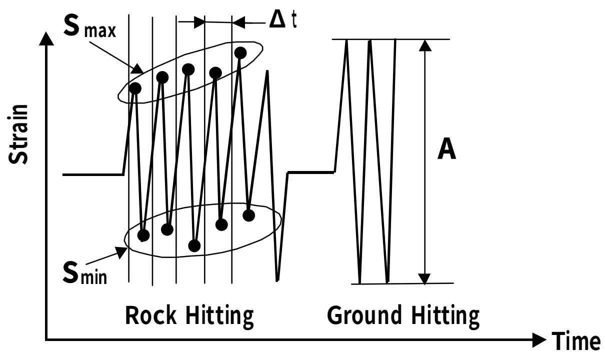

Fig.10 Determination of S_{max} and S_{min} in the time interval Δt

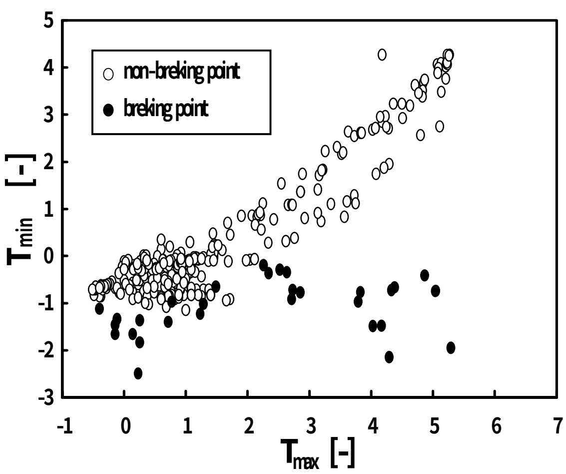

Fig.11 Relationship between T_{max} and T_{min}

Figure 11 shows the relationship between T_{max} and T_{min}. The white and black circles indicate the non-breaking point and breaking point, respectively. Totally, the experiment was carried out 31 times(14 times for the actual machine and 17 times for small model). Therefore, 31 breaking points were obtained and they were shown in Figure 11. Although some white and black circles are overlapped in the vicinity of (1, -1), it can be seen that white and black circles area are separated in this figure.

3.2 Pattern classification system

In this study, a neural network was used to make an intelligent judgement system for breaking the rock[5,6]. In this case, the input is (T_{max}, T_{min}) and the output is, for example, "1" for breaking and "0" for non-breaking. Therefore, the structure of the neural network as shown in Figure 12 was assumed in this study. The learning of multi-layer perceptron was conducted by back propagation method with teacher data. The learning was repeated 10,000 times.

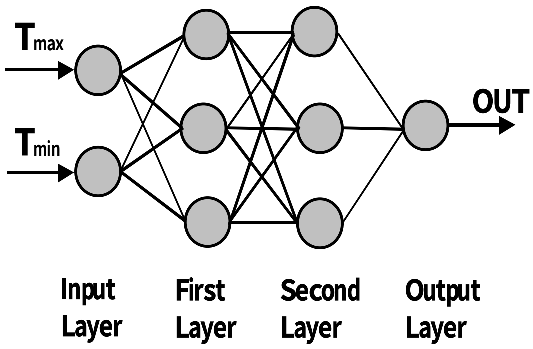

Fig.12 Structure of neural network used in this study

3.3 The map of breaking and non-breaking area

Figure 13 shows T_{max}-T_{min} map, which was calculated by using the neural network after learning. In this calculation, the output was classified into three areas such as breaking area (output >0.8), non-breaking area (output <0.2) and un-presumable area (0.2< output<0.8). It is confirmed that the border between breaking area and non-breaking area is not linear.

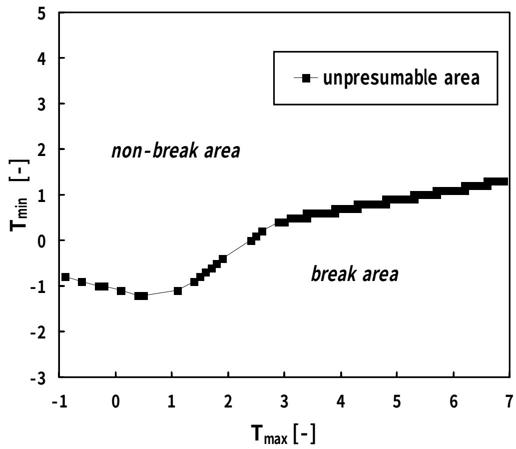

Fig.13 Relationship between T_{max} and T_{min} which was calculatedby use of the obtained neural network

4. CONTROL EXPERIMENT BY USE OF JUDGMENT ALGORITHM

The obtained neural network to judge the breaking was input into the computer, and the control experiment was carried out. In this experiment, the hitting was controlled to stop immediately when the rock is broken. The apparatus is the same as Figure 8. The Green tuff was used for this control experiment.

In the experiment, the strain data were measured while hitting the rock, and then (T_{max},T_{min}) was calculated and input into the neural network. Then, the output value was soon calculated. If the output is greater than 0.8, the hitting was automatically stopped by the computer. The control experiment was carried out 50 times. Therefore, 50 breaking points were obtained. Figure 14 shows the relationship between T_{max} and T_{min} at rock breaking. Black circles are included in the breaking area and this means that the judgment is successful. On the other hand, white circles are included in the non-breaking area in spite of the rock breaking and this means that the judgment is unsuccessful. That is, these circles mean that the machine continued hitting in spite of the rock breaking. The rate of success was 72%. There are some reasons why the machine continued hitting in spite of the rock breaking. One of the reasons is the insufficient database, which were used to construct the neural network. Therefore, the neural network is reconstructed by using all data with including 50 data obtained in the control

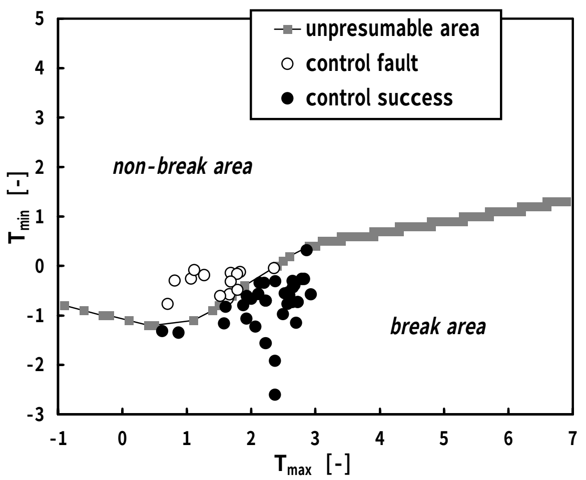

Fig.14 Relationship between T_{max} and T_{min} at rock breaking

experiment. In this case, the rate of success was 80%. The possibility of misjudgment is still high in the vicinity of (1,-1), but the algorithm constructed here almost works well. In the next step, the intelligent judgment system by using force sensors, vision sensors and some others is expected, however, it can be considered that the judgment system by use of force sensors is useful for the intelligent judgment system.

5. CONCLUSIONS

(1) The large tensile or compressive strain was obtained at rock breaking. This signal can be used to judge the rock breaking.

(2) The neural network was constructed to judge the rock breaking. The input signals are T_{max} and T_{min}, which was calculated from the measured strain data. The output is the judgment result. It was found through the control experiments by use of constructed neural network that the rate of success is 80%. In the next step, the intelligent judgment system by using force sensors, vision sensors and some others should be investigated.

ACKNOWLEDGMENT

This study is financially supported by Japan Limestone Association. We would like to express our appreciation for their financial support.

REFERENCES

Sensors and Control for Mining Robotics, Proc. of 4th Int. Symposium on Mine Mechanization and Automation, pp.6-9 1997.

[2]H.Takahashi and K.Sano : Automatic Detection of Large Rocks by Image Processing, Journal of the Mining and Material Processing Institute of Japan, Vol.113, No.3, pp.169-174, 1997.

[3]H.Takahashi and K.Sano : Automatic Detection and Breaking System for Large Rocks by Image Processing, Proc. of 4th Int. Symposium on Mine Mechanization and Automation, Vol.1, pp.27-34, 1997.

[4]H.Takahashi, K.Sano and E.Nakano : Study on Automatic Detection and Breaking System for Huge Rocks by Use of Image Processing --- Obtaining the Three Dimensional Information of Huge Rock Position for Breaking Task --- Journal of the Mining and Material Processing Institute of Japan, Vol.114, No.8, pp.543-548, 1998.

[5]R.Beale and T.Jackson : Introduction to Neural Computing, Kaibundo Publisher, pp.14-30, 1993.

[6]I.Hayashi and T.Furuhashi : Fuzzy/Neural Network, Asakurashoten, pp.1-11, 1996.