Multi-Modal Diagnostic Method for Detection of Concrete Crack Direction Using Light-Section Method and Hammering Test

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Abstract – Recently, many concrete social infrastructures are beginning to reach the end of their useful lives. Therefore, it is important to evaluate their condition. In this paper, we propose a method of concrete crack direction detection using visual and audio sensors. Firstly, three-dimensional measurement of the concrete surface is performed by using the light-section method. The obtained point cloud data is analyzed and the positions of the cracks are detected. Next, the positions to hit with a hammer are decided based on the crack position information. Finally, the acoustic signal is analyzed to detect the direction of the crack beneath the surface. Experimental results showed that the proposed method accurately detected crack position and crack direction.

Keywords – 3D scan, Hammering test, Learning, Sensing

1. Introduction

Nowadays, a large number of social infrastructures are beginning to reach the end of their useful lives. Therefore, appropriate maintenance and management are necessary for the social infrastructures. Figure 1 shows an example of inspection work for maintenance of a tunnel. There are some problems: first, many skilled inspectors are needed for inspection, because the inspection area is so wide. Secondly, labor shortage occurs as the skilled inspectors retire. Thirdly, a lot of sites, which were impossible to inspect in the past due to their dangerous location have became inspection target. In order to solve these problems, it is necessary to develop an automatic diagnostic method.

Focusing on concrete structures which occupy a large part in the social infrastructures, exfoliation is one of abnormal condition of which early detection is desired in the automatic maintenance and diagnosis. Exfoliation is a phenomenon in which concrete pieces are peeled off from the surface layer of a structure, causing fragments falling. It is dangerous because the dropped concrete pieces could damage vehicles and pedestrians passing under and inside the structures in the case of bridges and tunnels. Therefore, inspection and diagnosis are essential for the concrete structures.

One of the major causes of the exfoliation is a crack closure of the multiple cracks that have entered obliquely to the concrete surface. Figure 2 shows such crack closure on the concrete. Especially, concrete members that cause an exfoliation from the crack closure can become large concrete blocks, and the damage increases. Therefore, it is important to detect cracks at an early stage and to investigate the direction of entry in order to prevent the occurrence of fragments falling in advance.

In the conventional inspection site, hammering test [1-7] have been conducted to detect the defect from the different impulsive sounds generated when the object is hit with an inspection hammer. This method has the advantage that it is more efficient and accurate than other inspection methods. Focusing on the automation of hammering test, many automatic diagnostic methods of hammering test have been proposed [3-7]. However, there remains a problem that the method can not identify the direction of crack on the concrete surface.

In this study, we propose a multi-modal diagnostic method that combines the crack detection method using the light-section method with the automatic diagnostic method using hammering test in order to detect the direction of crack on the concrete surface.

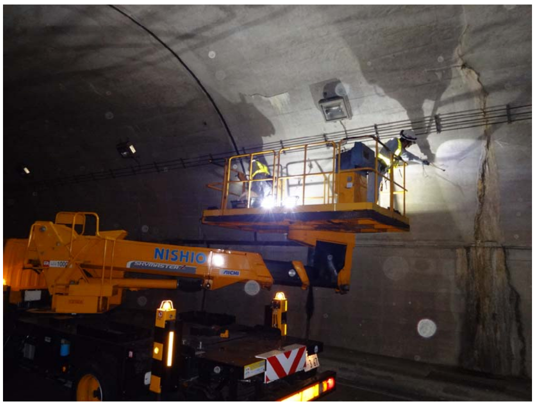


Fig. 1. Inspection by professional workers.

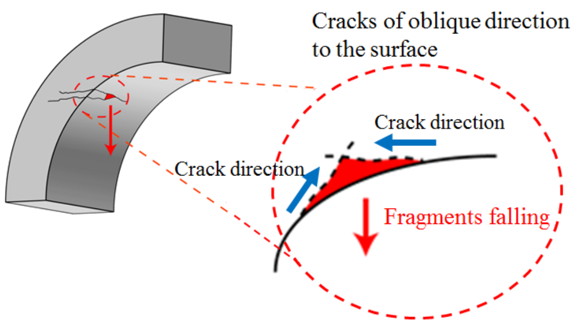


Fig. 2. Crack closure on the concrete.

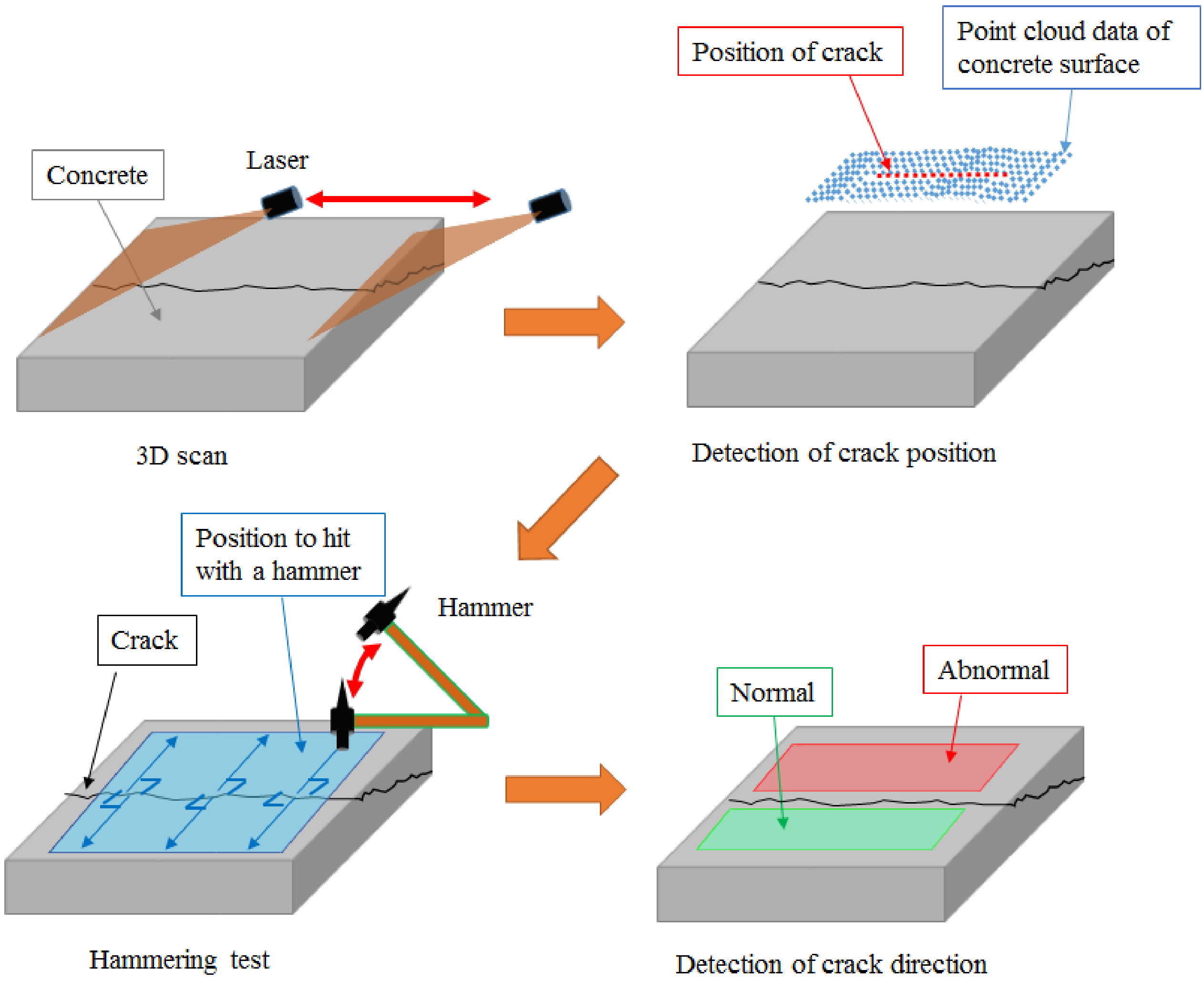


Fig. 3. Flow chart of proposed method.

2. Related Researches

In this section, we introduce some automatic diagnostic methods which use visual sensor or sound sensor. As the conventional crack detection methods using a visual sensor, there are some methods of detecting cracks on the concrete surface by analyzing an image acquired from a camera using machine learning [8-10]. However, these methods have a problem that is black lines are erroneously recognized as cracks in this method. To solve these problems, 3D measurement method using a laser is used for detecting cracks on the concrete surface [11,12]. Although these methods can detect the crack positions visible on the concrete surface, it is impossible to detect the direction of cracks.

On the other hand, there are concrete crack detection methods using a sound sensor. One of such sensor is ultrasonic waves [13,14]. Although this method can measure up to the depth of cracks, there is a problem that accuracy varies greatly depending on measurement conditions. There are other methods based on hammering test [15-17]. These methods are based on acoustic analysis. However, the convetional hammering tests have a problem that the results of crack detection change due to individual difference.

In order to solve these problems, our research group has proposed automatic method by hammering test based on supervised learning [18,19]. These methods can detect cracks inside the concrete. However, as stated in the introduction, it is impossible to estimate the direction of cracks by our conventional methods. In order to solve this problem, we propose a detection method of concrete crack direction. The method integrates the light-section method which is able to detect the crack positions with high precision and the hammering test which is able to detect the cracks existing inside the concrete.

3. Proposed Method

3.1 Concept

In this research, we propose a method to detect the direction of concrete cracks using light-section method and hammering test. Figure 3 shows a flow chart of our

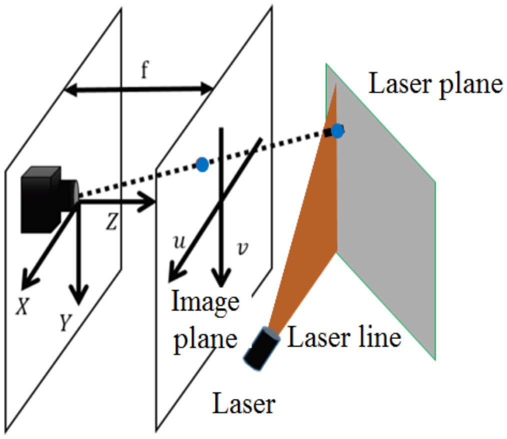


Fig. 4. Relationship between laser projection point and image coordinates.

proposed method. The proposed method consists of four steps. At first, three dimensional measurement of the concrete surface is conducted by using the light-section method and point cloud data of the concrete surface is acquired. Secondly, the acquired point cloud data is analyzed and the position of the crack is detected. Thirdly, acoustic signals are obtained by hitting the around the crack with a hammer. Finally, the direction of cracks on the concrete surface is detected by analyzing the obtained acoustic signals. Every step will be described in detail in the following sections.

3.2 Three-dimensional Scan

We use the light-section method which can measure with high accuracy the crack on the concrete surface. Figure 4 shows relationship between laser projection point and image coordinates. For calculating the three dimantional coordinates, two equations $z = ax + by + x$, $[x, y, z]^{\mathrm{T}} = \lambda[u, v, f]^{\mathrm{T}}$ are used. The former represents the laser plane. The latter represents the relationship between laser projection point and image coordinates, where x, y, z are three-dimensional coordinates of the laser plane. u, v are two-dimensional coordinates in the image plane. λ is parametric variable and f is focal length. a, b, c are parameters that can be calculated by camera calibration. The four unknowns parameters x, y, z and λ are calculated by solving simultaneous equation about two equations. As the result of this calculation, the point cloud data of concrete surface is acquired.

In this research, by scanning the object surface with a slit laser, the shape of the whole surface of the object is measured. The laser is fixed on the linear guide and camera is fixed in front of the object. The Camera callibration is performed before scanning.

3.3 Detection of Concrete Crack Position

For the detection of concrete crack position from acquired point cloud data, Canny edge detection algorithm [20] which can detect edges with low error rate is used. Before applying Canny edge detection algorithm, point

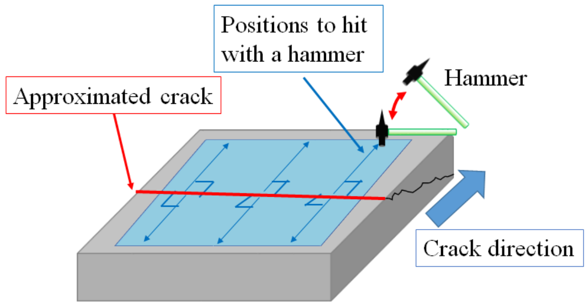


Fig. 5. Positions to hit with a hammer.

cloud data are converted into depth image. As a results of these processes, an image which shows the crack positions is acquired. In this study, we assumed that the cracks are generated by a cold joint. The cold joint is a phenomenon found in many tunnels that are currently subject of inspection. The cold joint is a plane of weakness in concrete caused by an interruption or delay in the concrete hardening or poor construction. When concrete cracks are generated by cold joint, the crack can be approximated to a straight line. For this reason, the crack which is detected by Canny edge detection algorithm is approximated to a straight line.

3.4 Hammering Test

Before hammering test, positions to hit with a hammer need to be decide. In the case of cracks that entered obliquely to the concrete surface layer, the crack enters vertically upward or downward with respect to the crack detected on the concrete surface, because concrete cracks continuously enter the surface layer in a certain direction. Therefore, it is possible to discriminate whether the crack direction is upward or downward by hitting with a hammer along the vertical direction with respect to the crack on the concrete surface and comparing the upper and lower acoustic signals. Figure 5 shows the positions to hit with a hammer. The positions to hit with the hammer is defined as a constant interval in the direction perpendicular to the crack.

In order to distinguish between normal and abnormal, time-frequency analysis [19] is used. In this method, a plurality of partial frequency bands capable of accurately distinguishing between normal and abnormal are extracted and integrated from the hammering sound signal analyzed in time frequency. By applying an ensemble learning technique, the method integrates plural detectors (weak learners) that can deal with their own respective frequency sub-band. In the following parts, let symbol D denote variables regarding defect, and let symbol C be used for describing variables regarding clean, which means defect free. Each weak learner has a linear discriminant function to classify the clean and defect samples as follows:

$$\boldsymbol{m}^{\mathrm{T}}\mathbf{S} + \theta = 0, \tag{1}$$

where $\mathbf{S} = [{}^{C}\mathbf{S}, {}^{D}\mathbf{S}]^{\mathrm{T}}$, $\boldsymbol{m}$ denotes the coefficient vector, and θ denotes the bias, both of which must be designed for each weak learner. Detection of defects by $\boldsymbol{x}$ that each weak learner $h(\boldsymbol{x}) \in \{-1, 1\}$ performs is as follows:

$$h(\boldsymbol{x}) = \begin{cases} 1 & \text{if } \boldsymbol{m}^{\mathrm{T}}\mathbf{S} + \theta \geq 0 \\ -1 & \text{otherwise} \end{cases} . \tag{2}$$

For example, when $h(\boldsymbol{x}) = 1$, the sample is defective. A weak learner diagnoses the material condition by focusing on its own specific frequency sub-band. In order to deal with various material defects, which have different characteristics in the frequency domain, improvement of both accuracy and robustness is quite significant. For this purpose, this method uses ensemble learning techniques. With respect to material defect detection, for accurate diagnosis, it is necessary for weak learners to obtain their variety by focusing on the sub-band different from another. In order to construct such weak learners, this method generates weak learners in sequence according to a boosting algorithm and integrates them into a whole detector (strong learner). The strong learner $H(\boldsymbol{x})$ can be expressed as follows:

$$H(\boldsymbol{x}) = \sum_{t=1}^{T} \alpha_t \,\mathrm{sign}[h_t(\boldsymbol{x})] \Big/ \sum_{t=1}^{T} \alpha_t \,, \tag{3}$$

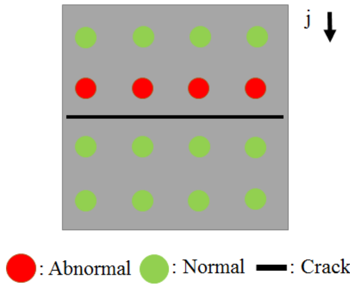
where α_t denotes the confidence coefficient of each weak learner as computed by the error ratio. The output of the strong learner is expressed as a type of defective score by normalizing it in the range of [-1, 1]. That is, the higher $H(\boldsymbol{x})$ is, the more is the hammered diagnostic target suspected of a defect. For example, in the case that the plus or minus sign of $H(\boldsymbol{x})$ is adopted as a defect criterion, the defect detection can be treated as an output of the binary classification $H(\boldsymbol{x})^* \in \{-1, 1\}$ as follows:

$$H(\boldsymbol{x})^* = \begin{cases} 1 & \text{if sign } [H(\boldsymbol{x})] \geq 0 \\ -1 & \text{otherwise} \end{cases} . \tag{4}$$

As a result of the hammering test, normal and abnormal areas are determined.

3.5 Detection of Concrete Crack Direction

Crack direction is detected using results of hammering test. Figure 6 shows concept of detection of crack direction.



i →, j ↓

0	0	0	0
1	1	1	1
0	0	0	0
0	0	0	0

(a) (b)

Fig. 6. Concept of detection of crack direction: (a) Results of discrimination between abnormal and normal, (b) Mathematical expression of the result of (a).

As the results of hammering test, it is possible to identify the positions of abnormal and normal such as Fig. 6 (a). By defining abnormal=1, normal=0, it is possible to represent abnormal and normal positions by mathematical expression as shown in Fig. 6 (b). Equation (5) is used for detection of crack direction.

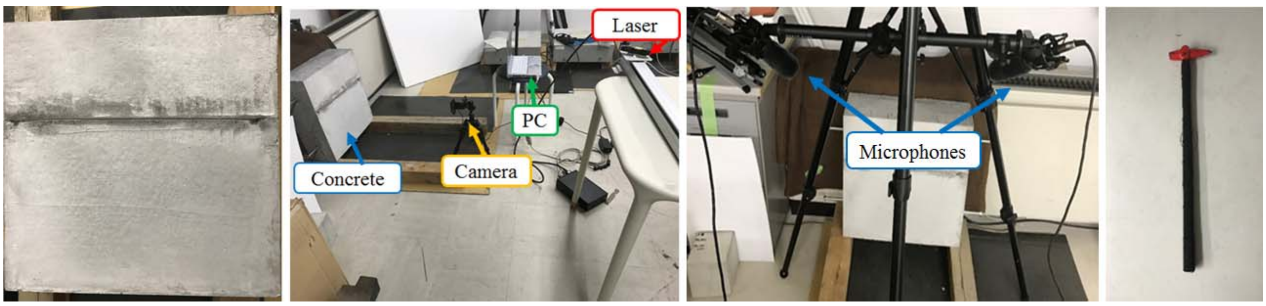
$$\text{Direction} = \begin{cases} \text{upward} & \text{if } \sum_{i=1}^{m} \sum_{j=1}^{\frac{n}{2}} x(i,j) > \sum_{i=1}^{m} \sum_{j=\frac{n}{2}}^{n} x(i,j) \\ \text{downward} & \text{if } \sum_{i=1}^{m} \sum_{j=1}^{\frac{n}{2}} x(i,j) < \sum_{i=1}^{m} \sum_{j=\frac{n}{2}}^{n} x(i,j) \end{cases} \tag{5}$$

where $x(i, j)$ is the value at coordinate (i, j). If the sum of the values in the upward direction with respect to the crack is larger than the sum of the values in the downward direction, the crack direction is determined upward. Inversely, if the sum of the values in the downward direction with respect to the crack is larger than the sum of the values in the upward direction, the crack direction is determined downward.

4. Experiment

4.1 Experimental Environment

For the experiment, concrete test piece with a size of 500 mm×500 mm×170 mm, a crack width of 1mm and an entry direction of 30 degrees was used. Figure 7 (a) shows



(a) (b) (c) (d)

Fig. 6. Experimental environment: (a) Concrete test piece, (b) measurement environment, (c) measuring instrument, (d) inspection tool.

the concrete test piece. The concrete test piece was crafted for the experiment and the ground truth of the concrete test piece was also known. For 3D measurement, DAVID's 3D Scan Kit was used, the used camera was Logitech Webcam Pro 9000 (resolution 640×480, 30 fps), the laser used red line light (wavelength 650 nm). Figure 7 (b) shows the measurement environment. The camera and the laser were fixed at a distance of 0.5m and 1m respectively from the concrete. The laser was fixed on the linear guide and the laser was moved at a speed of 20 mm/s during measurement. It took about 25 seconds for one scan. Figure 7 (c) and (d) shows a measuring instrument and an inspection tool. An inspection hammer made of iron having a head diameter of 12.4 mm and a head weight of 0.1 kg was used as an inspection tool. Two channel omni-directional condenser microphone was used as a measuring instrument, and the resolution was 24 bits and the sampling rate was 48 kHz. A PC with Intel Core^{TM} i5-2520M CPU 2.5 GHz PC was used for calculation.

4.2 Experimental Result

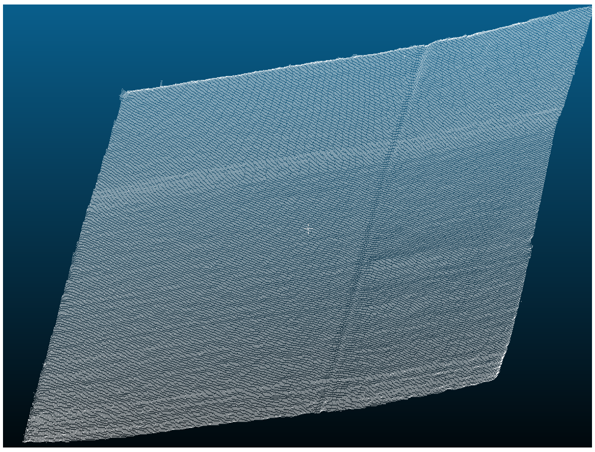


Fig. 8. Experimental result of three-dimensional scan.

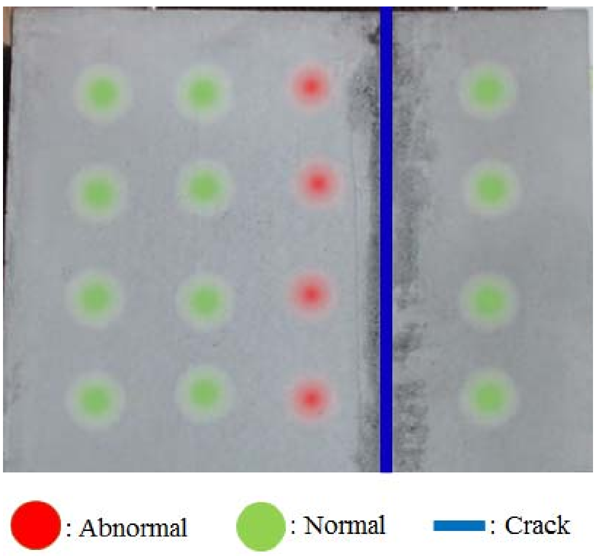


Fig. 9. Experimental result of hammering test.

Figure 8 and 9 describe the experimental result of three-dimensional scan, crack detection and hammering test respectively. As the result of three-dimensional scan, point cloud data of concrete surface was obtained as shown in Fig. 8. The point cloud data was converted to depth image and the crack position was detected by applying Canny edge detection algorithm to the depth image. The white area represent the crack position and the black areas represent normal position. As the result of the hammering test using the crack position information, normal and abnormal positions were identified as shown in Fig. 9. Red circles, Green circles and blue line indicate abnormal positions, normal positions and position of crack respectively. As the result of crack detection, the crack was distributed longitudinally at the center of concrete. The right side of the crack was detected as a normal areas. On the other hand, abnormality was detected near the left side of the crack and normal was detected on the left side far from the crack. As the result of detection of crack direction, the crack direction was detected in the left direction with respect to the detected crack.

We evaluated the experimental result with real 3D CAD data of the concrete test piece which was used in experiment. Figure 10 shows CAD data of the concrete test piece. Red line represents real position of crack. Orange areas represent abnormal areas. The upper part of the Fig. 10 shows the plan view and the lower part of the Fig. 10 shows the front view. The concrete which was used in this experiment had crack of 30 degrees and 170 mm length with reference to the concrete surface. The crack direction was left direction with respect to the crack. This means that the crack direction which was detected by proposed method and actual crack direction were same.

5. Conclusion

In this study, we proposed the multi-modal diagnostic method that combines the crack detection method using the light-section method with the automatic diagnostic method using hammering test in order to detect the

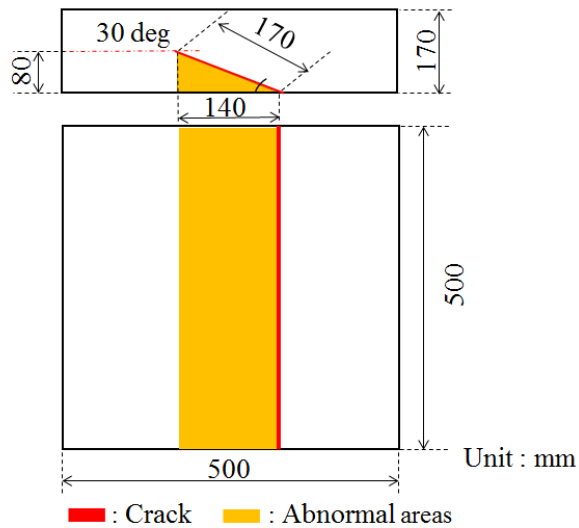


Fig. 10. CAD data of concrete test piece.

direction of crack on the concrete. The experimental results showed that the proposed method accurately detect crack position and crack direction. For future work, we plan to verify our method on actual field.

Acknowledgement

This work was supported in part by Council for Science, Technology and Innovation, "Cross-ministerial Strategic Innovation Promotion Program (SIP), Infrastructure Maintenance, Renovation, and Management" (funding agency: NEDO), JSPS KAKENHI Grant Number JP16H06680, and Institute of Technololgy, Tokyu Construction Co., Ltd.

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