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A Neural Network Algorithm for Detecting Invisible Concrete Surface Cracks in Near-field Millimeter-wave Images

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***Abstract*— Using near-field millimeter-wave imaging, we have developed a nondestructive inspection tool called "Crack Scan" to detect concrete surface cracks of sub-millimeter width. In this paper, we propose a new image-processing algorithm based on a cross-coupled neural network, which enables Crack Scan to detect invisible cracks in blurred images. We demonstrate that our algorithm can detect a 0.2-mm-wide crack under a ceramic tile on-site.**

***Keywords*—Millimeter-wave imaging, neural network, crack detection, nondestructive inspection.**

I. INTRODUCTION

Decrepit concrete structures, such as expressways built many years ago and recently built apartment buildings with shoddy construction, are becoming serious problems. In assessing the durability of concrete structures, inspection for surface cracks is crucial. As shown in Fig. 1, when cracks appear on a concrete surface, water and air can penetrate the concrete and attack the reinforcing steel inside, thereby corroding it and reducing the strength of a concrete structure. To prevent this sort of deterioration, it is very important to detect and repair these surface cracks as early as possible. In order to assess the extent of cracks that must be repaired, crack width at the surface is often measured. Though the allowed crack width slightly differs according to the criteria of each country, it is generally about 0.3-0.4 mm in dry air, or a little less than that in humid air. Many experts agree that cracks with a width of 0.2 mm or more should be repaired with filler material [1].

When a concrete surface is exposed, cracks can be detected by visual inspection. In buildings, however, the walls are often covered with paint, wallpaper, and repairing material, which makes it difficult to detect surface cracks by visual inspection. When visual inspection is not possible, X-rays or ultrasonic waves, which can pass through the obstructing material, are usually used. However, it is difficult to use X-rays when the opposite side of the target object is not accessible, because the transmitting and receiving sensors must face each other. There are also safety concerns when using X-ray equipment, and operators have to have special qualifications. For ultrasonic waves, the practical problem is that inspecting a wide area with ultrasonic probes is very time-consuming. For these reasons, it has been difficult to use existing technologies to detect surface cracks in unexposed concrete.

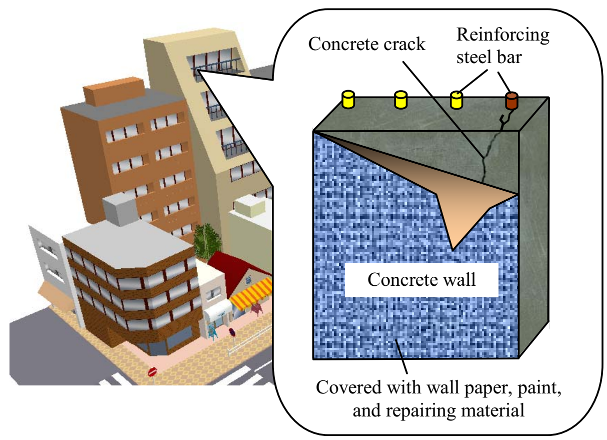


Figure 1. Deterioration of concrete structures by cracks

Against this background, we have studied millimeter-wave imaging to develop a unique technology for detecting concrete surface cracks. Millimeter waves are electromagnetic waves which have a wavelength in the millimeter range (frequency from 30 to 300 GHz) and can penetrate materials like clothes and plastics. In recent years, this property has been used to develop some imaging applications, such as security gates at airport and aviation monitoring systems [2-4].

On the other hand, we have proposed the idea of exploiting the features of near-field imaging. While the spatial resolution of quasi-optics millimeter-wave imaging systems, such as security cameras, is limited to several millimeters by the wavelength, the spatial resolution of our imaging system reaches sub-millimeter order by capturing the dispersion of millimeter waves in the near field. Using this approach, we have developed a nondestructive imaging tool called "Crack Scan" for detecting fine surface cracks in concrete structures [5].

However, this Crack Scan still has a fatal problem. In tests of Crack Scan for on-site inspection, we have found that it is very difficult for users to find cracks by watching the monitor.

This is because the contour of cracks in the millimeter-wave image is too blurred to recognize their shape due to the noise reflected from the aggregates in concrete. When crack width is less than 0.2mm, the contour is almost invisible. In this paper, we briefly describe Crack Scan, and then propose an image processing algorithm to solve this problem. Our algorithm uses a cross-coupled neural network that can reveal invisible cracks in blurred images.

II. CRACK SCAN

A. *Principal and configuration*

Millimeter-wave imaging methods can be categorized into two general types: passive imaging, in which millimeter-waves radiated from an object itself are detected, and active imaging, in which the object is illuminated with external millimeter-wave radiation and the reflection or transmission is detected. For example, warm objects like the human body emit black-body radiation including millimeter-band waves, so passive imaging can be applied to detect concealed items under clothes by using the human body as a backlight (a source of millimeter-wave radiation) [6]. On the other hand, objects like concrete structures do not emit detectable amounts of millimeter waves, so an active imaging method using external millimeter-wave radiation is required [7].

The basic principal of crack detection by millimeter waves is shown in Fig. 2. When millimeter waves are directed at a concrete surface at an angle, the waves are reflected from smooth areas in a one direction, while the reflection from edges of cracks randomly scatters in all directions [8]. Thus, if the transmitter and the receiver are positioned opposing each other, cracks can be detected by measuring the intensity of the reflection.

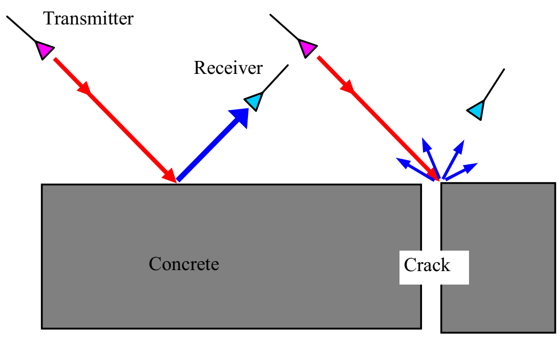


Figure 2. Surface reflection on concrete

Fig. 3 shows the basic configuration of active millimeter-wave imaging. The Gunn diode generates millimeter-waves, and the transmitter antenna is directed at the concrete wall surface and emits a millimeter-wave. This millimeter-wave is amplitude-modulated with a TTL of frequency from several tens to hundreds kilohertz. The center frequency of millimeter-wave is 76.5 GHz and the output power is under 10 mW. The detector uses Schottky-barrier diodes to detect the reflection from the concrete surface. The intensity of the reflection is measured by the filter board, and digitized with an A/D converter. Fig. 4 shows the system design of Crack Scan. A key component of this design is an arrayed detector. Obtaining an image by scanning with a single detector in two dimensions would be time-consuming, so we created a one-dimensional array of detectors to enable fast scanning. The number of detectors is 32, and the aperture of a receiver antenna is 1.6 mm. The digitized signal is sent to a PC and synchronized with the encoder distance signal. Then, a 2D image of the concrete surface is shown on the monitor. The operator holds the main unit to scan the concrete surface and can identify cracks in real time by observing the scanned image on the monitor.

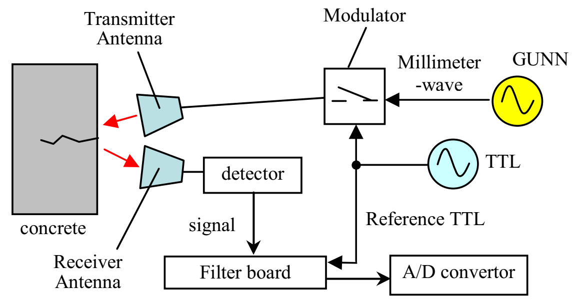


Figure 3. Configuration of active millimeter-wave imaging

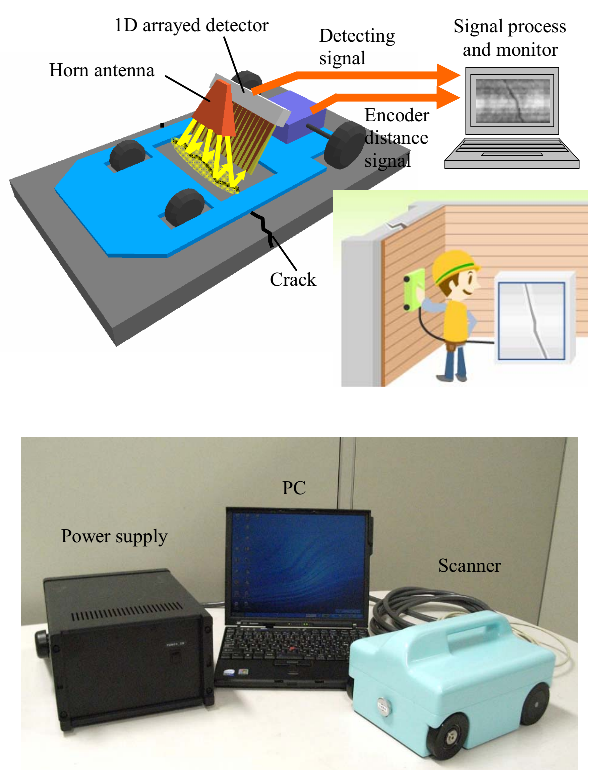


Figure 4. System design of Crack Scan

A trademark application for Crack Scan has been submitted by NTT.

B. Physical limit of resolution

The Crack Scan can reliably detect cracks of 0.3-0.4 mm width. However, even with near-field imaging, it is sometimes difficult to find cracks of 0.2 mm width or less which should be repaired with filler material.

Fig. 5 shows an example of millimeter-wave images obtained with Crack Scan. On the surface of the concrete sample, there is a crack of 0.2 mm wide [Fig. 5(a)]. We covered the crack with 7-mm-thick ceramic tile and scanned over it, but the output image is too blurred to find the crack [Fig. 5(b)]. This problem is caused by the compositional non-uniformity of concrete. Generally, a concrete block contains a lot of aggregates [Fig. 6(a)]. Since the millimeter wave penetrates the concrete surface to a depth of about a half an inch, signals reflected from the crack and the aggregates are mixed together. Therefore, we cannot identify the crack signal only from its intensity [Fig. 6(b)].

In order to identify this fine crack, we have to add other information, that is, "shape" in two-dimensional space, and this is why the image processing approach is required for the detection of fine cracks. Generally, line profile of a crack has a unique contour with a certain length.

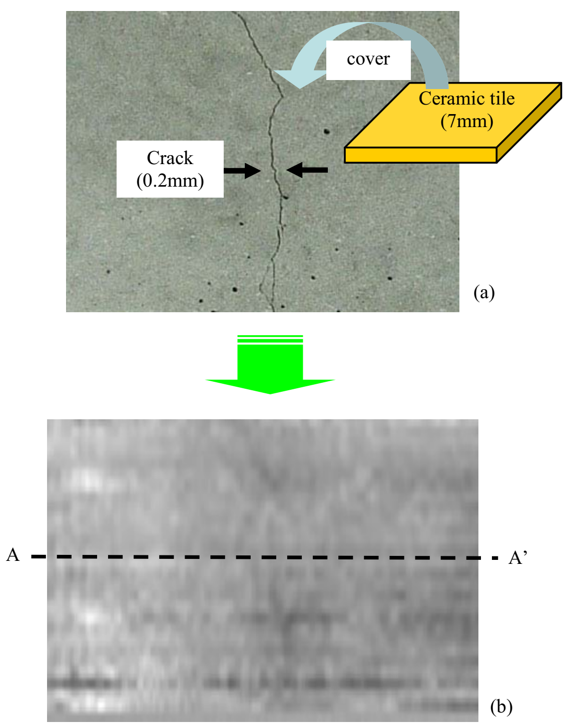


Figure 5. Millimeter-wave imaging of concrete surface crack. (a): CCD image of sample, (b): Millimete-wave image (95 x 70 mm)

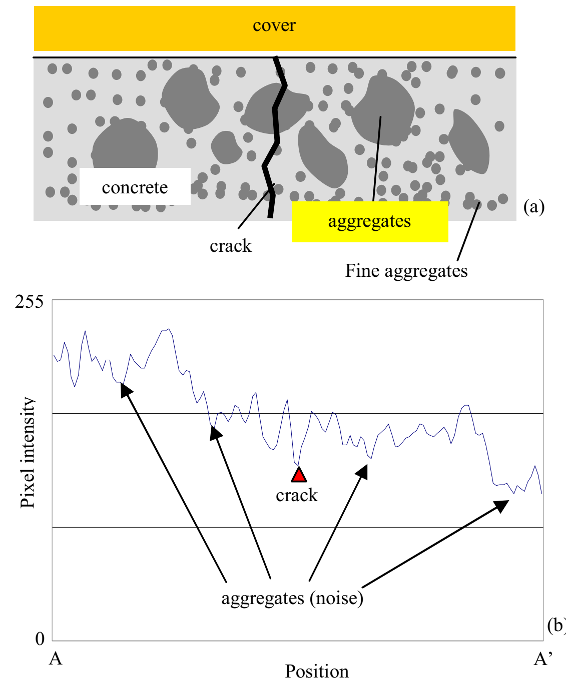


Figure 6. Invisibility of crack in millimeter-wave image. (a): Compositional non-uniformity of concrete, (b): Pixel intensity

III. Neural Network Algorithm

To detect cracks in a millimeter-wave image, we use a cross-coupled neural network model [9-10]. We represent the crack detection problem using an x×y neuron array as shown in Fig. 7, where x and y are the size of pixels in the input image.

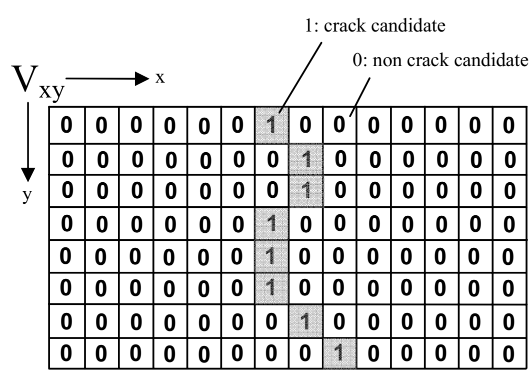


Figure 7. Neural network representation

Calculation Steps

1. Initialize the input of neurons U with uniform random values.

2. To update the new output values, use the input-output function

$$V_{xy}(t+1)=1 \quad if\ U_{xy}=\max\lfloor U_{ky}(t);\forall:k\rfloor, \\ 0 \quad otherwise \tag{1}$$

where U_{xy} is the input to the xy th neuron, and V_{xy} is the output. $V_{xy}=1$ when the xy th pixel is considered as a crack, and $V_{xy}=0$ otherwise. I_{xy} is the intensity of xy th pixel. This update rule is called the “winner-take-all neuron” or “maximum neuron” [11-12].

3. For each neuron, update input U using the first-order Euler’s method:

$$U_{xy}(t+1)=U_{xy}(t)+\Delta U_{xy} \tag{2}$$

where

$$\Delta U_{xy}=\alpha\cdot p(x,y)-\beta\cdot q(x,y) \tag{3}$$

$$p(x,y)=\sum_{m=x-M}^{x}\{I_{m-1,y}-I_{m,y}\}+\sum_{m=x}^{x+M}\{I_{m+1,y}-I_{m,y}\} \tag{4}$$

$$q(x,y)=\sum_{b=y-B}^{y-1}\|(x,y)-(a,b)\|+\sum_{b=y+1}^{y+B}\|(x,y)-(a,b)\|, \tag{5}$$

$$where \quad V_{ab}=1$$

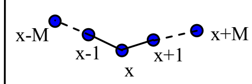
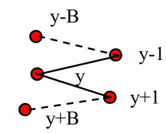
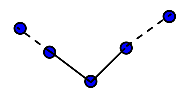
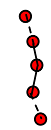
$\|(x,y)-(a,b)\|$ is the Euclidian distance between pixel (x,y) and (a,b).

4. Go to step 2 until the status of V converges to equilibrium.

Table 1 illustrates how the functions p(x,y) and q(x,y) work. The p(x,y) returns the gradient of edge along the x axis direction; when the gradient is steeper, this function returns a larger value. On the other hand, q(x,y) returns the smoothness of the connection between crack candidate pixels; when the connection is smoother, this function returns a smaller value. By updating each V_{xy}, this neural network converges to an equilibrium state so that ΣU_{xy} reaches the largest value.

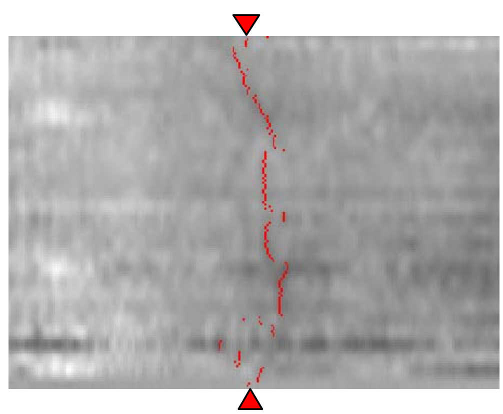
Note that this algorithm searches cracks along the y axis in an input image, where the allowed detectable crack angle is 45 degree. Therefore, the second search for the 90 degree rotation is required in order to complete the crack detection process.

TABLE I. TWO FEATURES OF CRACK

	p(x,y) : Gradient function	q(x,y) : Smoothness function
Non-crack	p(x,y) is small 	q(x,y) is large 
Crack	p(x,y) is large 	q(x,y) is small 

IV. SIMULATION RESULT

Fig. 8 shows a simulation result when the image in Fig. 5(b) was used as an input image. The 0.2-mm-width crack under the 7-mm-thick ceramic tile was automatically detected. The size of the image is 245×200 pixels, and the intensity is 8-bit gray-scaled. Parameters α and β in (3) were set at 0.325 and 1.0, M in (4) was set at 20, and B in (5) was set at 20 respectively. Using Pentium4 (3.0GHz) personal computer, this simulation converged in two seconds.



Detected crack

Figure 8. Result of image processing

V. CONCLUSION

Surface crack detection is very important for assessing the deterioration of concrete structures. Millimeter-wave imaging is a unique approach for inspecting cracks in covered concrete surfaces. Our image-processing algorithm can reveal invisible cracks of 0.2-mm-width or less in real time. In addition to ceramic tile, we verified that our algorithm properly worked for various kinds of covering materials, such as fiber-reinforced plastic, glass, and rubber. As future works, we will try to use the near-field millimeter-wave imaging in other application fields such as food inspection.

ACKNOWLEDGMENT

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