DEFECT DETECTION FOR RC SLAB BASED ON HAMMERING ECHO ACOUSTIC ANALYSIS

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Abstract

Hammering test, as a conventional non-destructive test method, is widely applied for concrete structure inspection for decades. The method is based on monitoring the acoustic reaction of the surface resulting from a short-time physical impact, i.e. hammering. Hammering test is usually performed by field workers based on individual experience to assess the condition. Thus, it is subjective judgment rather than objective evaluation. To tackle such problem, this paper proposes condition-based assessment method for concrete hammering through analyzing echo acoustics, attempting to detect deep flaws inside the structure. We employ novel spectral feature and Grassmann manifold learning for condition assessment. And we conduct real-world data validation with testing concrete structures. Testing result validated the proposed method.

1. Introduction

Aging bridge infrastructure poses severe pressure to human society. After several decades in service, the robustness of bridge structures became weak, especially our construction becoming old, i.e. about half the length of the approximately 300km in-service expressway has been opened for more than 30 years, especially traffic condition becoming worth, i.e. increase of the heavy vehicles caused damage to our road. To enhance the stability of aging infrastructures, maintenance and replacement are common measures to take. As the front stage of all measures, Nondestructive testing (NDT) plays a key role in assuring the adequacy of bridge components, and has been a core research area for decades. As one conventional NDT method, the impact-echo test, that investigates stress wave generated by mechanical impact, had been extensively applied for flaw detection in concrete infrastructures. The initial literatures describing impact-echo was presented from 1970s [Achenbach, 1973]. And later, more studies were carried out in both theoretical and experimental aspects [Sanalone et. al, 1986; Casino et. al, 1986]. While, practical application of the method starts much earlier before it was coded in book. The mechanism of impact-echo is demonstrated with following chart.

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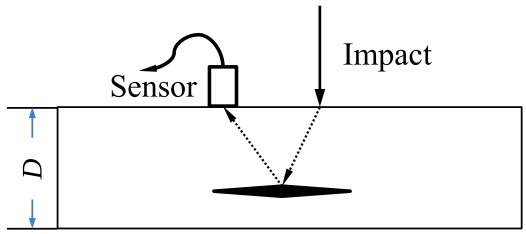

Figure.1 Demonstrate of impact-echo method

According to above chart, conventional impact-echo can be described as follows; an impact is applied to the concrete surface. A sensor is employed to capture the resonance introduced by impact from surface. By investigating the resonance signal in spectral domain, the flaws can be detected. For echo signal spectral analysis, a well-defined formula is induced to determine a void beneath surface of concrete [Frank S., Bernd K. 2008]:

$$d = \frac{BK}{n}\frac{C_p}{f} \tag{1}$$

where f is peak frequency of echo spectrum, C_p is P-wave velocity, B is so called "Lamb wave" correction factor, and n is a constant factor depending on the acoustic impedances. and d denotes depth of inner defect. To facilitate engineering usage of impact-echo technique, imaging methods for impact-echo test had been investigated and air-coupled sensor is applied to speed up the inspection [Zhu J.Y. 2007]. In recent, more research effort are focusing on employing more advanced signal processing methods to characterized defect-induced anomaly in echo signal, such as using empirical mode decomposition (EMD) [Y.Zhang 2012]. However, the complexity of advanced method may hinder the efficiency for inspection. In this study, we utilize effective spectral analysis method for characterizing hammering impact-echo signals [Jiaxing Ye et. al 2014]. The feature is based on echo Fourier spectrogram and thus mature fast algorithm can be used. In addition, the feature favorably captures condition-related patterns in echo signal. In section 2.1, we will give throughout introduction to the echo feature extraction. Based on echo feature representation, in section 2.2, we further investigate the echo pattern corresponding to condition of hammering position. To validate the proposed method, we conduct experiments on real-world data and exhibit the results in section 2.3. The results demonstrated the effectiveness of the method.

2. Scheme for condition-based hammering echo signal analysis

In this study, we employ automatic condition-based assessment method [Jiaxing Ye et. al 2014] for concrete structure through analyzing the impact-echo signal of hammering. There are two main components in the proposed system: feature extraction and statistical pattern analysis for condition evaluation. We present overall flowchart in Fig. 2.

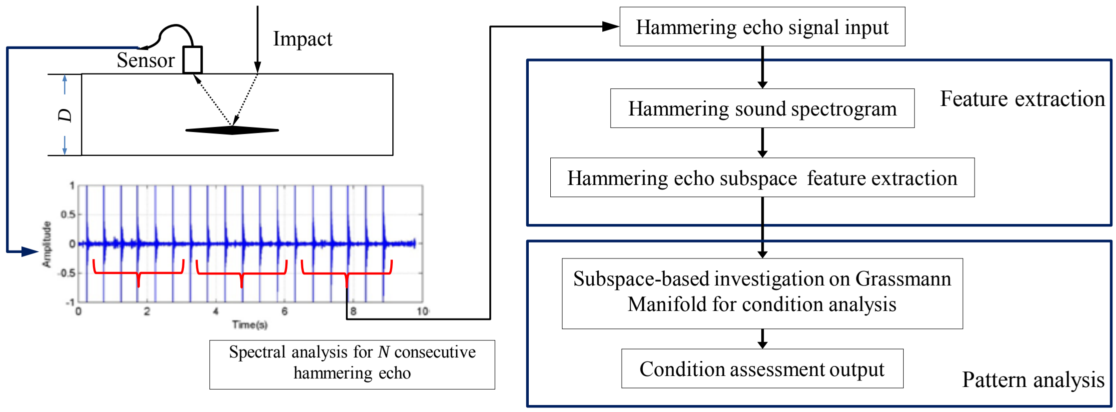

Figure.2 Flow of chart of the hammering test method

2.1 Feature extraction for hammering sound

In this section, we present the feature extraction scheme for hammering acoustics. As conventional approach, time-frequency analysis has been extensively used for impact-echo, which proceeds through the Fourier transform [9]. To extract feature from continuous hammering responses, we adopt STFT to produces the time-frequency spectrogram of acoustic signal [Mitrović, D. 2010] and set basis for further advanced analysis. The Fourier transform is defined as:

$$F_x(t, f) = \int_{-\infty}^{\infty} x(\tau) e^{-j2\pi f \tau} d\tau. \tag{2}$$

where $x(t)$ is echo waveform to be analyzed, which would be expanded over a series of cosine waves via Fourier transform. Subsequently, we conduct effective feature extraction based on echo spectrogram.

Unlike conventional impact-echo using peak frequency of echo spectrum, we utilize subspace feature representation for echo. In machine learning field, subspace analysis has been active topic in recent decade [Hamm, J. 2008]. Based on theory that low-dimensional subspaces can empirically approximate both the structural distribution and variations, data is represented as a collection of subspaces and further investigation can be subsequently performed. The representative successful application is face recognition under varying lighting conditions and poses [Shakhnarovich, G. 2011]. We apply our previous scheme to adopt subspace feature for echo signal with mainly three benefits: 1. The predominant variation patterns in echo signal can be effectively characterized, including the spectrum peak that is proved to be effective in earlier literatures; 2. In addition to peak frequency, subspace feature is favorable for extracting such 2-D dynamic structures; and thus more rich temporal-spectral patterns can be captured. 3. Lower dimensional subspace is much more efficient for processing, comparing to full data spectra. All these issues laid the basis for echo signal feature extraction. The detailed process can be explained as follows.

Let $x = [x_1, x_2, \cdots, x_n], x_i (i = 1, \cdots, n) \in \mathbb{R}^M$ denote ($M \times n$) spectrogram of hammering echo signal and n denotes the time frame indexes, M stands for uniform-bank scale frequency. To extract the echo signal subspace, we calculate eigenvalues $\Lambda = diag(\lambda_1, \cdots, \lambda_M)$ and eigenvectors $U = [u_1, \dots, u_M]$ by:

$$R_{Cov_x} U = U \Lambda, \qquad R_{Cov_x} \triangleq \mathop{E}_{i=1}^{n} \left\{ x_i x_i' \right\}, \tag{3}$$

where $x_i', i \in (1, \cdots, N)$ is transpose of x_i. We sort eigenvectors by eigenvalues in decreasing order. These eigenvalues manifest the significance of corresponding eigenvectors for reconstructing the input signal. The contribution rate of η_K is defined as:

$$\eta_K \triangleq \sum_{i=1}^{K} \lambda_i \Big/ \sum_{i=1}^{M} \lambda_i \,. \tag{4}$$

All eigenvectors of $U_M = [u_1, \dots, u_M]$ ($M \times M$) support the subspace encoding temporal-spectral pattern of hammering acoustic. Particularly, basis vectors in U_M is ranked by the contribution for representing echo. Dominant structural information always lies in first several principal vectors. And hence, we can select first several basis vectors to form echo subspace, i.e., N basis as $U_N = [u_1, \dots, u_N]$, $1 < N < M$ to concentrate on predominant patterns in echo signal and remove the noise influence simultaneously.

The selection of principal basis vectors is crucial for classification performance. From information coverage aspect, having more principal vectors means covering more patterns of the echo waveform. However, holding more principal vectors may include noises that lead to deterioration in condition-based analysis performance. We experimentally tested 80 hammering sound clips to determine the number of principal vectors to employ. The result is shown in Figure 3. Based on it, we select first 12 principle basis vectors to represent echo signal for further analysis on Grassmann manifold. And in the FFT, we set the Fourier analysis window length to 256 points. As a result, we compress the 256 dimension data to 12 dimensions. The processing efficiency is significantly improved.

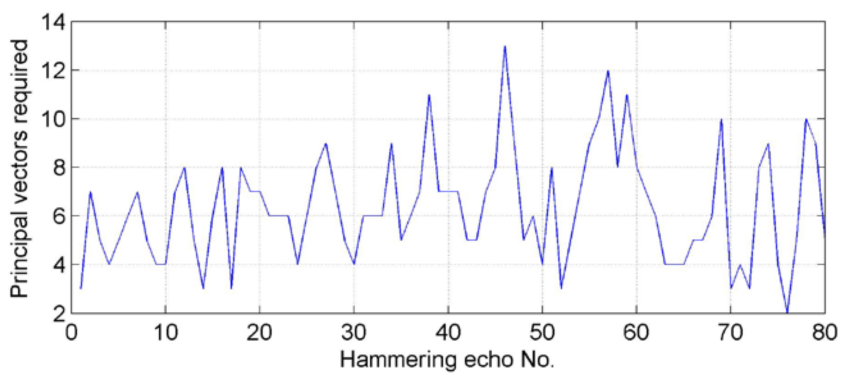

Figure.3 The required number of basis for recovering 99% patterns of echo signal

2.2 Condition-based assessment based on statistical analysis

Grassmann manifold is dedicated for investigating subspace-to-subspace relations, such as distance/similarity measures. It was initially discussed in linear algebra [P. Absil et al 2006] and subsequently put into some practical applications [T. Kim, 2007]. Based on abovementioned subspace feature extracted from hammering echo, we analyze the distance between hammering echo subspaces on Grassman manifold. As a supervised method, at training stage, both data and labels are input. Then, we can define normal pattern region in the feature space through constructing boundary criterion on Grassmann manifold. Therefore, based on the distance measure on Grassmann manifold, we can indicate to abnormal patterns corresponding to flaw existence.

An effective distance metric on Grassmann manifold is critical for application. Let Y_1 and Y_2 be two orthonormal $D \times k$ matrices, for instance two hammering sound subspaces. In Grassmann learning, one most applied metric is geodesic length connecting the two corresponding points of Y_1 and Y_2. It is also named as principal angles/canonical correlations denoted by $0 \le \theta_1 \le \cdots \le \theta_1 \le 2\pi.$ And it can be computed recursively by

$$\cos\theta_m = \max_{u_m \in span(Y_1)} \max_{v_m \in span(Y_2)} u_m' v_m, \quad \textit{subject to}$$

$$u_m' u_m = 1, v_m' v_m = 1, \; u_m' u_n = 0, v_m' v_n = 0, (n = 1, ..., m-1). \tag{5}$$

where ($u_1, u_2, ..., u_m$) and ($v_1, v_2, ..., v_m$) are the basis vectors of two subspace and θ_m is angle between subspaces. The distance between two subspaces Y_1 and Y_2 can be examined by a series of principal angles $\theta = [\theta_1, ... ,\theta_k]$. From the Grassmann manifold viewpoint, the subspaces span(Y_1) and span(Y_2) are two points on the manifold $\boldsymbol{G}(k,D)$, whose Riemannian distance is related to the principal angles by $d(Y_1, Y_2) = \|\theta\|$ [P. Absil et al 2006]. We present a chart to demonstrate such idea in Fig. 4. The smaller principal angles that manifest the subspaces are closed to each other. In addition to primitive principal angles, several Grassmannian distances have been proposed, such as max correlation $2\sin^2\theta_1$ and projection distance $\sum\sin^2\theta_i$ [Hamm J. 2008], etc. They are mostly deducted from principle angles. In this study, we employ principal angles for condition based analysis of hammering echo signals. Based on training data of normal hammering sounds, we can measure the pairwise similarity between samples, which can be expressed as:

$$\cos\theta_{12} = \mathrm{sim}(S_1, S_2) \tag{6}$$

where S_1 and S_2 are any samples from training dataset $S = [S_1, ... ,S_N]$. function of sim(.) is defined by (5). The threshold for detecting anomaly patterns in hammering test is defined as:

$$\text{Threshold}_\theta = \sum_{i=1}^{N}\sum_{j=i}^{N} \cos\theta_{ij} \Big/ \sum_{n=2}^{N}(n-1) \tag{7}$$

Based on threshold criterion, we investigate input data through characterizing principal angles. If input data present small principal angles to training data, it will be determined as normal pattern, because it closes to training patterns. On the other hand, if distinctive principal angle is generated, the input data corresponded area will be recognized as flaw.

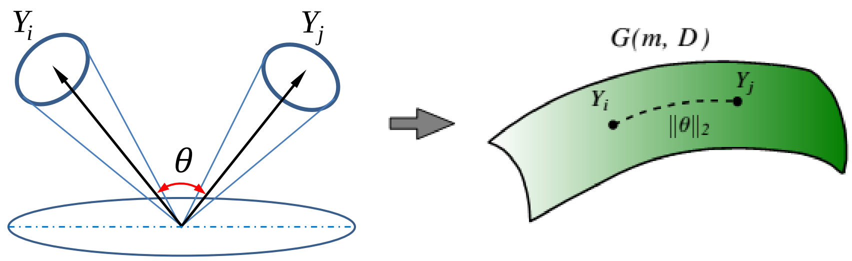

Figure.4 Demonstration of subspace-to-subspace distance on Grassmann manifold

3. Experiment on testing concrete structure

In this section, we validate the proposed method with real-world data. The testing data capture and parameter settings are explicitly presented. Also discuss over experimental results is shown. Firstly, we introduced the testing concrete structure we prepared for the test through Figure 5. There are various defects area on the structure, such as different size voids and cracks; the depths are varying as well. The detail structure of concrete is exhibited with following design chart. Notably, the right half of concrete is with carbon-fiber sheet reinforcement. And such sheet is challenging for hammering test analysis because the echo signal is disturbed.

3.1 Data capture

We performed line-based hammering on the concrete structure shown in Fig. 5. Notably, there are two types of concrete surfaces in the concrete structure; in detail, left half is ordinary concrete surface and right half is covered by carbon-fiber sheet for enhancement. We collected training and testing hammering data separately for two types of concrete surfaces, because the sheet significantly affects echo signal patterns. For instance, on right half with enhancement sheet, we randomly performed hammering test on areas without defects to build training set. Subsequently, we hammered over line 3 and 4 to capture test data. For left half of ordinary surface, we use same scheme to collect training and test data.

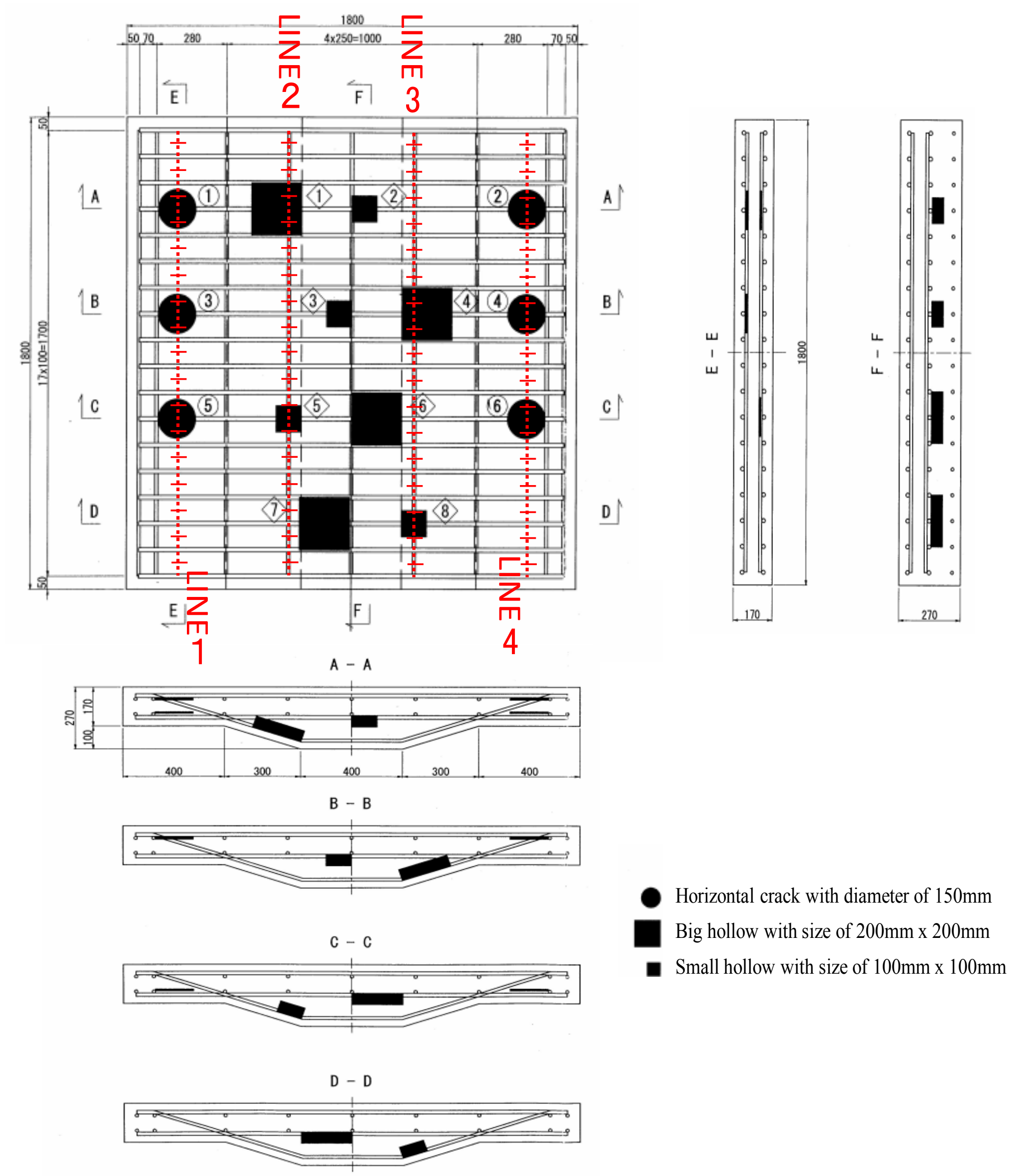

Figure.5 Design chart of concrete structure with right half covered by carbon-fiber sheet

3.2 Parameters

For hammering sound analysis, we set Fourier analysis window length to 50ms with 25ms overlapping in Short-time Fourier Transform (STFT). A high pass filter is adopted to remove low frequency noise below 400Hz. We extracted K = 12 principal eigenvectors with highest contribution ratio to form audio representation, from which over 99% of patterns in sound are accommodated according to their contribution ratios (4).

3.3 Results and discussions

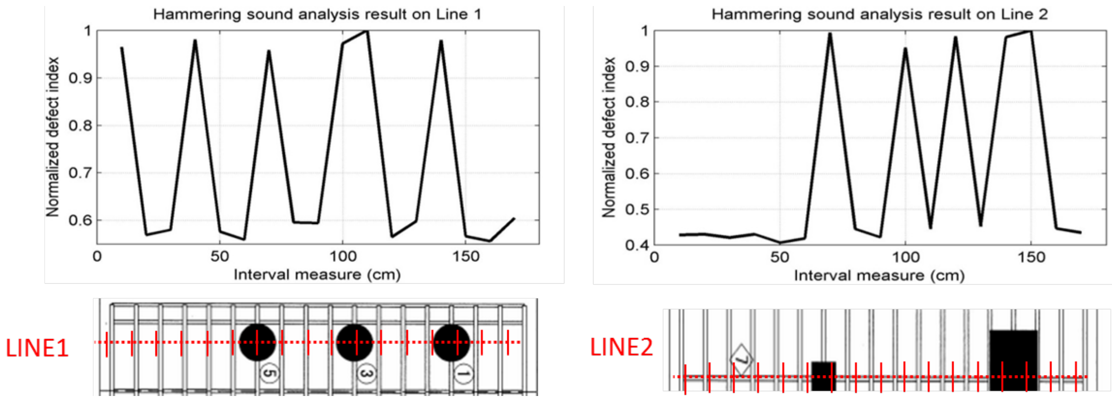

Figure.6 Result for ordinary concrete hammering test on LINE 1 and 2.

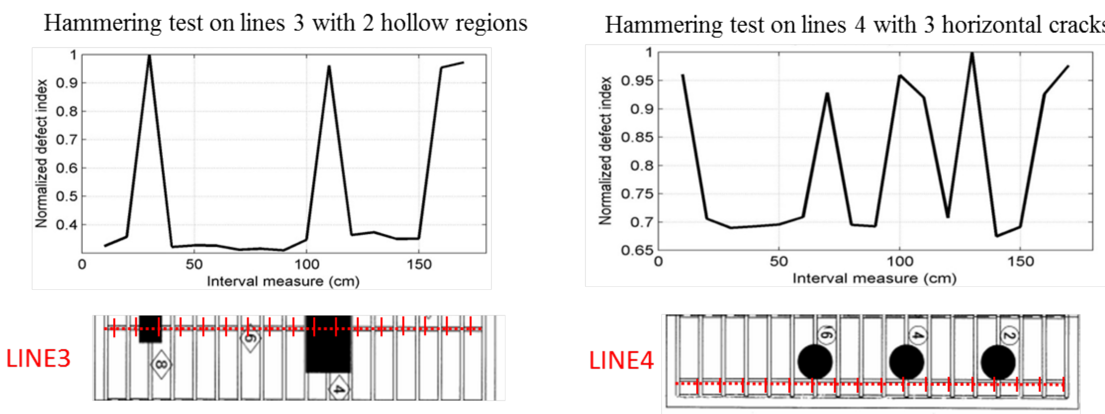

Figure.7 Result for hammering test on concrete with carbon-fiber sheet on LINE 3 and 4.

Based on statistical analysis approach presented in section 2.2, we conduct condition-based investigation on testing hammering data. The results are shown separately, because different training data is applied behind. Fig. 6 presents results of hammering data collected from line 1 and 2 and they are over all ordinary concrete surfaces. Fig. 7 illustrates analysis result on carbon-fiber enhanced areas of line 3 and 4.

According to above result, the method is validated for condition-based analysis for concrete slab. Notably, it works stably for even for the case that carbon-fiber enhanced sheet is applied. There were some false alarms issued in the test for non-sheet-covered area. Both hollow and crack can be detected due to the anomalous patterns reflected in hammering sound. Besides, hammering position affects the hammering test result. Edge of concrete structure has some changes comparing to the central area, the reason is that the reaction patterns of hammering strength waves are different (edge/central). And thus some false alarms are generated during edge hitting. It would be one practical issue to be considered for real applications. The evaluation result demonstrated effectiveness and efficiency of the propose approach. However, as a preliminary method, more detail settings would be further determined, such as spectral feature selection with filter banks and discriminant analysis with more labelled data.

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