Statistical Impact-Echo Analysis Based on Grassmann Manifold Learning: Its Preliminary Results for Concrete Condition Assessment

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STATISTICAL IMPACT-ECHO ANALYSIS BASED ON GRASSMANN MANIFOLD LEARNING: ITS PRELIMINARY RESULTS FOR CONCRETE CONDITION ASSESSMENT

Jiaxing YE[1], Masaya Iwata[1], Takumi Kobayashi[1], Masahiro Murakawa[1], Tetsuya Higuchi[1], Yuichi Kubota[2], Toshiya Yui[2], Kiyoshi Mori[2]

[1] *National Institute of Advanced Industrial Science and Technology, Tsukuba, Japan*
[2] *Shutoko Engineering Company, Tokyo, Japan*

ABSTRACT

Impact-echo is one extensively applied non-destructive technique for flaw detection in concrete structures. In impact-echo test, surface motion generated by short-duration mechanical impact is investigated for structural condition assessment. This paper endeavours to formulate impact echo analysis by using novel statistical techniques, i.e. Grassmann manifold learning. Comparing to conventional impact-echo test, the proposed method presents several favourable properties: 1. Conventional impact-echo method mostly relies on frequency peak in echo spectrum; the proposed method characterizes rich temporal-spectral patterns in addition to the spectral peak. 2. Proposed method is performed over local area on concrete surface with integration of several consecutive echo responses, and thus produces more stable condition evaluation result comparing to point-wise impact-echo approach. 3. To cope with extracted echo feature, effective similarity metric on Grassmann manifold is employed, which favourably facilities condition-based assessment. To demonstrate the proposed method, we prepared concrete specimen with 2cm, 4cm and 6cm depth void inside and echo signal is captured through air-coupled sensor. Experimental result demonstrates the effectiveness of the proposed method, including accurate condition-based classification performance and high processing efficiency

KEYWORDS : *non-destructive test, impact-echo, acoustic signal, time-frequency analysis, Grassmann manifold learning.*

INTRODUCTION

Maintenance, rehabilitation and replacement of aging civil infrastructures, i.e. bridges and highways, pose worldwide pressing problems to human society. Among all issues related to aging infrastructure management, condition inspection is the most critical one, since it is decision-making stage for further measures, and thus attracts lots of research efforts for decades. Impact-echo, as one most applied non-destructive test (NDT), has been extensively studied from both theoretical and numerical aspects since it was initially proposed in 1980s [1]. The basic mechanism of impact-echo is to assess health status of concrete through investigating transient stress wave induced by short-duration impact. Some commercial devices have been well-developed for impact-echo test [2], meanwhile, standard has been issued to promote utility of impact-echo method [3]. Based on those core works, impact-echo has been applied to various practical tasks, such as flaw detection of delamination, voids and debonding in concrete [2].

In this paper, we propose a novel data-driven impact-echo analysis approach aiming at producing high accuracy for detailed flaws pattern classification with objective evaluation protocol. The proposed approach formulates impact-echo analysis by introducing content-based recognition framework, in which responses from normal and flaws conditions are regarded as different patterns to be classified. The main contributions of proposed approach can be summarized as follows:

- The proposed approach is a data-driven and condition-based method with well-established objective for impact-echo investigation. Unlike conventional impact-echo investigation methods involving subjective judgment in interpreting test results [2], the proposed method is designed to produce direct condition-based assessment result which could facilitate non-expert usage.
- Conventional impact-echo analysis is usually conducted in frequency domain which addresses peak frequency for determining defects in concrete. The assumption laid behind is that an echo signal can be decomposed into various spectral components and the peak frequency of echo signal reflects the condition of concrete. From data representation viewpoint, it is a conversion from 1-dimension time-series to 1-dimension spectrum of echo signal. However, it is worth noting that by selecting smaller analysis window in Fourier analysis, more precise temporal-spectral information of echo signal can be observed which may contribute to condition analysis for concrete. Based on such 2-D time-frequency representation, we propose to employ subspace to effectively characterize the echo signal. The subspace of echo spectrogram is capable of exploring rich temporal-spectral pattern of echo signal in addition to spectral peak. In addition, since point-wise impact-echo may be severely affected due to elastic heterogeneity of (concrete) structure, the proposed feature extraction process is conducted in local area-based manner, in which several successive responses in adjacent area are integrated together to produce one echo subspace (feature) for further analysis. By doing so, isolated point elastic stiffness variations no longer affect assessment result much.
- Grassmann manifold learning is well developed for investigating subspaces [4]. Various effective distance metrics between subspaces are applicable in this formulation, which lay solid fundamental for investigating echo subspace features for condition-based impact-echo test. In this work, we introduce principle for selecting proper similarity metric for impact-echo test and further validate it with real data. The experimental results validate the propose formulation for impact-echo.

The rest of this paper is organized as follows. In Sec. 1 we briefly review the state-of-the-art of impact-echo method and in Sec. 2 we present details in proposed impact-echo analysis framework, including feature extraction from echo signal and Grassmann manifold learning for concrete structure condition assessment based on extracted echo feature. In Sec. 3 we demonstrate the proposed approach with real-world impact-echo data. A comparison has been made between using propose method and conventional one. Finally, we conclude this work in Sec. 4 with a discussion.

1 REVIEW FOR IMPACT-ECHO

Impact-echo is most widely applied non-destructive test method for concrete structure health assessment in nowadays. In an early summarization [2], impact-echo is described as follows: a hammer is first used to generate an impact on surface of concrete structure. Subsequently, a transducer is posed near the impact point to collect stress waves which propagate inside the structure. Then, signal analysis is performed on echo signal to determine the structural condition of concrete. The working scheme can be concisely illustrated in Fig. 1.

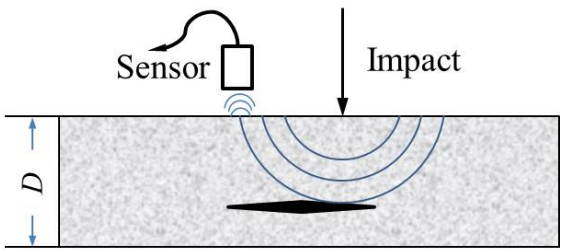


Figure 1: Illustration of impact-echo test using air-coupled sensor

Echo signal analysis is commonly performed through spectral analysis. Although several advanced time-frequency analysis techniques have been employed in recent studies, such as the Wavelet transform [5] to alleviate poor time-frequency resolution in Fourier spectra, Fourier analysis still dominates impact-echo analysis field due to simplicity of algorithm implementation and sharper echo peaks it produces, which is regarded as determinant measure for concrete assessment.

A well-known formula to determine a void beneath surface of concrete is proposed by [6]:

$$d = \beta C_p / 2f \tag{1}$$

where f denotes peak frequency of echo signal spectrum, $\boldsymbol{Cp}$ is the velocity of the longitudinal, β is constant of 0.96 for plate-shape structures wave [6] and d represents depth of inside void. In addition, to facilitate engineers' usage of impact-echo technique, imaging methods for impact-echo test attracted much research interests, such as in [7], a depth spectrum is proposed which interprets spectral peak of echo signal to depth of defect. Impact-echo is initially a contact inspection method, which is quite time-consuming and requires much human-effort to draw overall condition of large structures from points. To tackle the efficiency problem, a new suggestion is to apply air-coupled sensor for impact-echo [7]. A designated air-couple sensor is employed to capture acoustic echo from concrete structure. And experimental results show the air-coupled sensor is comparable to contact sensors for delamination detection and grouting quality evaluation tasks.

However, some recent studies reveal the availability of formula (1) is constrained by the size and flatness of defect area, e.g. if void is not parallel to surface, the echo resonance behaves differently and thus Eq. 1 fails to estimate void depth. [8] Until now, impact-echo method, which presents high diagnosis accuracy and favourable generalization property, remains to be challenging issue to non-destructive test field, and therefore, efforts will be continuously delivered to the topic.

2 GRASSMANN MANIFOLD LEARNING FOR IMPACT-ECHO

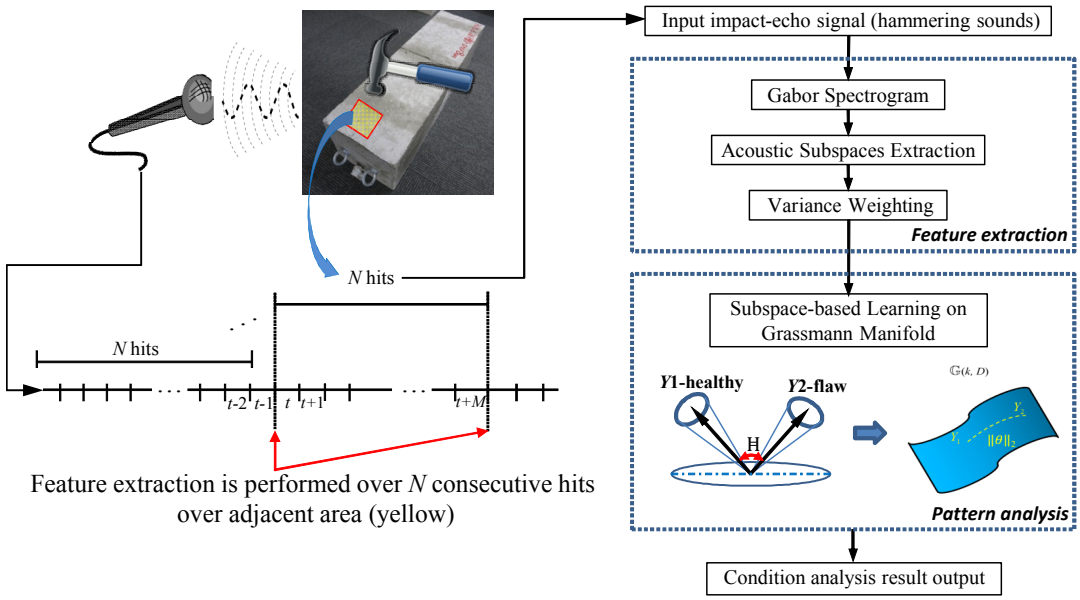


Figure 2: Working scheme of the proposed method

In this study, we employ air-coupled transducer to capture echo signal. The systematic scheme is shown in Fig. 2. The basic idea is that a "centered" echo feature is extracted from several consecutive impacts on local surface area and thus produce stable descriptive feature. To investigate the extracted echo feature, Grassmann manifold learning is introduced with effective similarity metric selection. The detail of the proposed impact-echo formulation is demonstrated in this section.

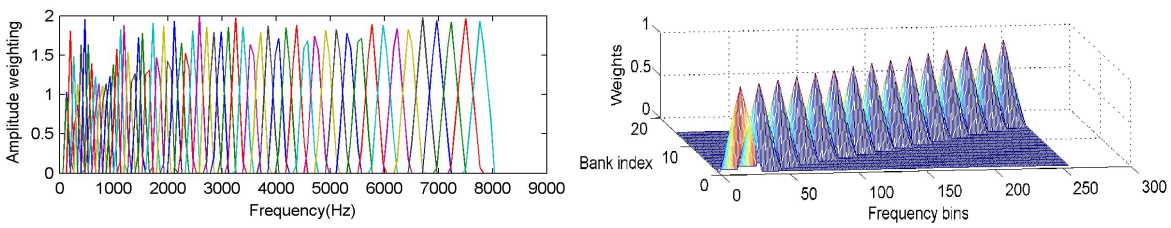
2.1 Feature extraction for impact-echo signal

- Time-frequency analysis has long the predominant approach for acoustic signal processing, and, one most effective tool is the short-time Fourier transform (STFT) [9]. STFT produces the time-frequency spectrogram of acoustic signal and facilitates further advanced signal processing. Gabor transform is an effective modification to STFT in order to realize best simultaneous resolution in both time and frequency domains. The Gabor transform can be expressed as:

$$G_x(t,f) = \int_{-\infty}^{\infty} e^{-\pi(\tau-t)^2} e^{-j2\pi f\tau} x(\tau) d\tau. \quad (1)$$

where x is echo waveform to be analyzed, and Gaussian window function is applied over the framed signal. We carry out effective feature extraction based on Gabor spectrogram of echo signal.

- **Fuzzy filter bank for spectrum** : To enhance robustness to noise, filter banks are usually applied in modern signal processing systems which designated to generate a concise but sufficient representation of a pattern with much lower dimension. Especially for audio signals, filter banks are well developed and extensively applied to alleviate the noise and interference in spectrogram. Among them, the most influential one is the Mel-bank [9]. It has been proved to be effective for approximating the human audition and widely applied for Automatic Speech Recognition (ASR) decades. We present an explanation chart of Mel-bank filter in Fig. 3 (1).



(1) Mel filter bank for speech (2) uniform-spaced filter bank for echo signal

Figure 3: Filter bank and uniform-bank for characterizing echo spectrum

In here, we follow Mel-filter bank's idea to design dedicated filter bank for characterizing impact response signal. Unlike in Mel-bank that unequal weights are assigned to each filter based on prior-knowledge of human hearing perception, in here, we adopt uniform-spaced filter bank coving full range of spectrum, which is presented in Fig. 3(2). We summarize the main considerations for applying uniform-spaced spectral filter bank: 1. Proposed filer bank preserved uniform discriminative resolution from raw power spectrogram, without bias emphasizing on particular bands. 2. The noise in spectrogram can be suppressed by sum-average over filter bank, making acoustic feature more stable. 3. Peak frequency can be enhanced by filter bank and thus facilitates defect investigation. 3. Comparing to power spectrogram, filtered spectrum is more efficient for handling with lower dimension and thus significantly accelerates the impact-echo test.

- **Subspace feature representation for echo signal** : In machine learning field, representing data as a collection of subspaces has been extensively investigated in recent decade [10]. Low-dimensional subspaces can empirically approximate both the structural distribution and variations in data quite well. For example, it has been widely accepted that a low-dimensional subspace is effective for encoding a set of images of face with varying lighting conditions and poses. We attempt to adopt subspace feature for echo signal from mainly three considerations : 1. From variations viewpoint, spectral peak can be well characterized which locates the maximum variation point over time-frequency plane; 2. In addition to abovementioned peak frequency, rich spectral-temporal distribution representation of echo signal which may also contribute to defect inference. Subspace feature is favorable for extracting such 2-D dynamic structures. 3. Comparing to processing the data spectra, manipulating lower dimensional subspace is much more efficient. All

these factors paved the basis for employing subspace representation for echo signal analysis. We present the detailed feature extraction procedure in follows.

Let $x = [x_1, x_2, \cdots, x_n], x_i (i = 1, \cdots, n) \in \mathbb{R}^M$ denote (M x n) filtered spectra by uniform-spaced filter bank 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,…,u_M] by:

$$R_{Cov_x} U = U \Lambda, \qquad R_{Cov_x} \triangleq \overset{n}{\underset{i=1}{E}} \left\{ x_i x_i' \right\}, \tag{1}$$

where $x_i', i \in (1, \cdots, N)$ is transpose of x_i. We sort eigenvectors by eigenvalues in decreasing order. These eigenvalues denote the significance of corresponding eigenvectors for expressing the spectrogram. The contribution rate of η_κ is defined as:

$$\eta_K \triangleq \sum\nolimits_{i=1}^{K} \lambda_i \Big/ \sum\nolimits_{i=1}^{M} \lambda_i \,. \tag{2}$$

All eigenvectors of U_M = [u_1,…,u_M] (M x M) span the subspace characterizing temporal-spectral distribution of echo signal. Particularly, basis vectors in U_M is ranked by the importance in representing the echo spectrogram and the dominant structural information would lie in first several basis vectors. Based on aforementioned specifications, we can select first several basis vectors from subspace, i.e., N basis as U_N = [u_1,…,u_N], $1 < N < M$ to concentrate on predominant patterns in echo signal and remove the noise influence simultaneously.

The selection of principle basis vectors is crucial for classification performance. From information coverage aspect, having more principle vectors means covering more patterns of the echo waveform. On the contrary, too few principle vectors of basis will certainly fail in depicting the echo. However, it doesn't mean holding the most principle vectors is always better since the intra-class variations and noise will be counted into feature which leads to deterioration in discriminant performance. Due to the fact that echo signal is usually presents an impulse-like spectra distribution, we experimentally select first 2 principle basis vectors to represent echo signal for further discriminant study on Grassmann manifold.

2.2 Grassmann manifold and distance for concrete condition assessment

Based on the subspace representation of echo signal introduced in last paragraph, we further determine a proper protocol to investigate the relationship between subspaces. Grassmann manifold learning is the right solution to tackle such subspace-based learning problems. In this section, we firstly outline the definition of Grassmann manifold; second, we introduce the Grassmannian distances and discuss principle for distance selection for impact-echo work.

- **Formulation of Grassmann manifold** : The linear subspace has been extensively studied and put into broad real-world applications, such as in face recognition [11]. However, the collection of linear subspaces forms a completely different space, which is specified as Grassmann manifold. As an effective mathematical tool for subspace-based analysis, Grassmann manifold has been recently introduced to signal processing field with successful applications [4]. We introduce the Grassman formulation for impact-echo test coping with uniform-filter bank-scale subspace representation of echo signal. Grassmann manifold $\boldsymbol{G}(k,D)$ is defined as the set of k-dimensional linear subspaces in the D dimensional space $\mathbb{R}^D$. For a Euclidean representation of the manifold, consider the space $\mathbb{R}_{k,D}$ of all matrices with identical D x k size. Consider the group of transformations $Y \rightarrow YL$, where L is nonsingular k x k matrix and $Y \in \mathbb{R}_{k,D}$. The group defines the equivalence relation of two elements in $\mathbb{R}_{k,D}$: $Y_1 = Y_2$, if span (Y_1) = span (Y_2), $Y_1, Y_2 \in \mathbb{R}_{k,D}$. Therefore the equivalence classes of $\mathbb{R}_{k,D}$ are in one-to-one correspondence with the elements of the Grassmann manifold $\boldsymbol{G}(k,D)$ and $\boldsymbol{G}(k,D)$ can be formed as the quotient space:

$$\boldsymbol{G}(k,D) = \mathbb{R}_{k,D}^{(0)} \big/ \mathbb{R}_{k,k}^{(0)} \tag{3}$$

The $\boldsymbol{G}(k,D)$ is an analytical manifold of dimension $Dk - k^2 = k(D-k)$, since for every Y regarded as a point in $\mathbb{R}_{k,D}$, the set of all elements YL in the equivalence class span the surface in $\mathbb{R}_{k,D}$ of dimension k^2. Based on the definition of Grassmann manifold, lots of properties have been deducted. Particularly, we focus on distance measures on Grassmann manifold for impact-echo test using echo signal subspace. The detail is introduced in following section.

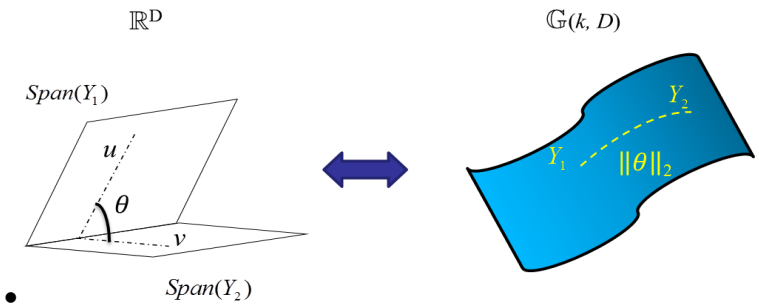


Fig. 4. Principal angles and Grassmannian distances.

- **Distance selection on Grassmann for impact-echo**: In this part, we address the distance metric selection on Grassmann manifold. In Grassmann learning, one most direct metric is the canonical distance describing the length of geodesic path connecting the two corresponding points on the manifold. It is also named as principal angles/canonical correlations. The definition is:

Let Y_1 and Y_2 be two orthonormal $D \times k$ matrices. The principal angles $0 \le \theta_1 \le \cdots \le \theta_1 \le 2\pi$ between two subspaces $span(Y_1)$ and $span(Y_2)$, are defined recursively by

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

$$u_m{}' u_m = 1, v_m{}' v_m = 1,\ u_m{}' u_n = 0, v_m{}' v_n = 0, (n = 1, \ldots, m-1). \tag{4}$$

The $(u_1, u_2, \ldots, u_m)$ and $(v_1, v_2, \ldots, v_m)$ are the basis vectors of two subspace and θ_m is metric between subspaces. We depict an explanation chart illustrating the subspaces distances in Euclidean space $\mathbb{R}^D$ and Grassman manifold $\boldsymbol{G}(k,D)$ in Fig. 4. In Fig.4, span(Y_1) and span(Y_2) are two subspaces in the Euclidean space $\mathbb{R}^D$ on the left. The distance between two subspaces Y_1 and Y_2 can be examined by the principal angles $\theta = [\theta_1, \ldots, \theta_k]$. 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 $d(Y_1, Y_2) = \|\theta\|$ [12]. The smaller principle angles that manifest the subspaces are closed to each other. In addition to primitive principle angles, several Grassmannian distances have been proposed, e.g., max correlation $2\sin^2\theta_1$, projection distance $\sum \sin^2\theta_i$ and Binet-Cauchy distance $1 - \prod \cos^2\theta_i$ [4], etc. They are mostly deducted from principle angles.

In this work, we adopt Arc-length Grassmannian distance, which is defined by:

$$d_{Arc}^2(Y_1, Y_2) = \sum_i \theta_i^2 \tag{5}$$

The Arc-length metric is derived from Grassmann manifold geometry and describes the length of geodesic curve linking two subspaces over the manifold. Our selection is based on following consideration: 1. to fully investigate similarities between echo-subspaces, it is better to evaluate all principle angles, not using single principle angle. Arc-length complies with such requirement, whereas max correlation and Procrustes distance that use smallest principle angle and Min correlation uses largest principle angle doesn't. 2. As distance measure, symmetric property and triangular property are necessary, Arc-length also satisfies such properties. In section 3, we experimental validated our selection.

3 EXPERIMENTAL VALIDATION WITH REAL DATA

To perform quantitative evaluation of proposed approach, we prepared three defect concrete blocks with 2cm, 4cm, 6cm depth hollows inside and one solid block. Ordinary MIC is used to capture responses of hammering impact over concrete. For every echo data sample, it is 1.5 second length sound including 3 consecutive hits. Subspace feature is extracted on every to generate stable pattern with regard to concrete condition. In Fig.5, we present an illustration of the extracted features, from which the condition-based discriminant power of the proposed feature can be clearly demonstrated. The subspace features forms several clusters corresponding to concrete conditions. In addition, we conduct comparative experiment by using peak echo frequencies of echo. The test data is the same as used in last test. The result is shown in Fig. 6 and in the result chart, and based on observation; there is no clear boundary in peak frequency measures for each condition of concrete. Notably, the last 5 echo for normal concrete were captured by hitting the area close to the edge which sounds differently comparing to the central parts of concrete. Therefore the peak frequencies vary sharply as marked in red. In contrast, such within-class variation doesn't affect result produced by the proposed approach. Final condition-based assessment results are summarized by statistical test.

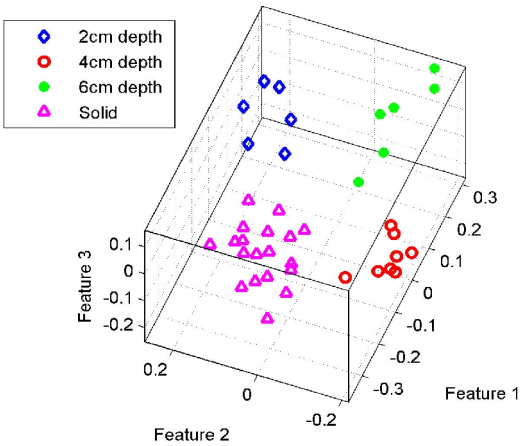


Figure 5: Condition-based echo signal classification result

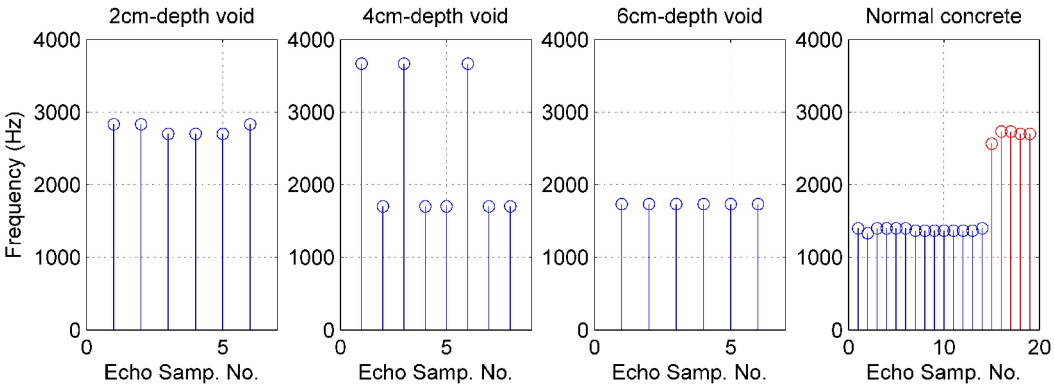


Figure 6: Peak frequencies extracted from hammering echo on concretes

At condition assessment stage, we employ principal angles to measure similarities between response signal on Grassmann Manifold and Leave-one-out (LOO) protocol is applied for statistical evaluation. According to Tab. 1, Echo signal corresponding to four conditions of concrete can be distinguished perfectly by the proposed method. Meanwhile, by comparison, the proposed approach significantly outperformed the conventional method using peak frequency of echo.

Table 1: Summarization of condition-based assessment results

Conditions	Solid	2cm depth void	4cm depth void	6cm depth void
Sample No.	19	6	8	6
Peak freq. reco. rate	73.68	50%	62.5%	100%
Proposed method reco. rate	100%	100%	100%	100%

CONCLUSION

In this work, we present novel formulation for impact-echo analysis. Unlike conventional impact-echo relying on peak frequency in spectrum of echo signal, we introduce subspace representation to characterize temporal-spectral distribution of response waveform. There are several advantages in doing so: 1. subspace representation effectively characterizes prominent time-frequency 2D distribution patterns of echo signal in addition to the frequency peak applied in conventional impact-echo. 2. Proposed method is conducted in local-region based manner including several consecutive echos, which produces more reliable results for concrete health assessment comparing to using point-wise method. 3. Grassmann manifold learning is designated for effectively measuring distances between subspaces, which is an ideal to work together with subspace feature in this task. We performed experimental validation on real data collection to validated the propose approach. Comparison results demonstrated effectiveness of the propose method. However, as a preliminary method, more detail settings would be further determined, such as perform band selection or importance weighting or introducing non-linear classification scheme with more data for more accurate condition-based assessment.

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