SENSORS and ACTUATORS A

Physical

Fuzzy pattern recognition of impact acoustic signals for nondestructive evaluation

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ABSTRACT

In order to prevent the danger caused by falling tiles from high-rise buildings, a rapid and effective non-destructive testing and evaluation (NDT&E) technique has been developed to assess the tile–wall bonding quality. The proposed technique is based on sounds excited by controlled impacts, and can easily be integrated with climbing robots to automate the tile–wall inspection process without the need for human workers to work at life-threatening height. To facilitate the result evaluation and maintenance planning, the approximate size of defective area needs to be assessed and determined. Though it is well-known that the natural frequency of flexural vibration is related to the size of the debonded area, strong multiple-mode frequencies caused by complex shapes of the defects or impacting at geometric edge (not at the center) of the defects impose significant difficulties in extracting automatically the natural frequency from the sound signals. In this paper, a fuzzy scheme is introduced to improve the robustness and accuracy of defects assessment. Based on fuzzy theory, vibration principle and human experience, a fuzzy logic model relating the characteristics of impact sounds to the approximate size of the defect is developed and utilized. The design of the fuzzy system, including membership functions and fuzzy reasoning rules, is also provided. To demonstrate the validity of the proposed method, experimental results obtained from physical tile walls are presented and discussed.

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1. Introduction

In highly developed metropolises like Hong Kong, tiles are used extensively on external walls of high-rise buildings for decoration and weather protection. Unfortunately, due to poor workmanship, atmospheric pollution and aging effects, the expected lifespan of tile adhesives is much reduced. This leads to an increasing number of accidents caused by tiles falling from tall buildings. As a result of this, there is an urgent need for an effective and efficient NDT&E method for inspecting external tile–walls of high-rise buildings. In view of such a demand, an impact acoustic method has been developed. The proposed method can easily be integrated with a climbing service robot [1,2] to automate the inspection process, which does not only improve the efficient of building inspection but also reduce the need for human workers to work at life threatening height. The automated detector, which conducts defect detection by impact sounds, is carried by a climbing service robot to move from one location to another until the entire building area of concern is covered.

As an established technique for inspection, impact sounds generated by tap test have been widely used for integrity assessment [3,4]. The principle of method is based on the fact that if two materials which are bonded together are impacted with a small hard object, the relative intensity and fundamental frequency of flexural vibration in the induced sounds will vary depending on the bond quality. The manual version of this method is simple and cheap, but is subjective and operator-dependent.

To remove the dependence on the human ear and subjective judgment, many efforts have been paid to automate the impact testing operation to develop a quantitative and low-cost nondestructive testing method for bonding defects identification. From the frequency distribution impact acoustics parameters, Asano et al. [5] derived a spectral feature based defects detection system. A similar investigation reported by Liu et al. [6] proposed to use the *sound intensity ratio*, which was calculated by the area of different bands in the power spectrum density (PSD) of the impact acoustic signals, to quantitatively identify the bonding defects of the tile–wall. Based on the theoretical analysis of the impact dynamics, Tong et al. [7,8] proposed tile–wall bonding state monitoring methods which employed the

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artificial neural network (ANN) classifier with features extracted from the PSD or time domain pattern of the impact acoustic signals. To alleviate the dependence on training samples, Tong et al. [9] reported a support vector machine (SVM) based tile–wall bonding state classifier, which also used the features extracted from the power spectrum density (PSD) as input. In another attempt to suppress the effects of noise, Luk et al. [10] developed an impact acoustic inspection method that utilized the wavelet domain features with hidden Markov modeling to achieve high performance in practical implementation under noisy environment.

Besides the bonding quality of the localized position associated with each impact, the overall size of the bonding defect is also an important criterion for practical result evaluation because only the bonding defects with a size bigger than 200 mm × 200 mm are considered to be dangerous, and are required immediate repair. However, while the problem of bonding defect identification has drawn a lot of attention, few works have been performed to utilize impact acoustic sounds to estimate the approximate size of the bonding defect. According to sound and vibration theory [11], for sounds emitted from debonded structures, it can be theoretically concluded that the corresponding fundamental flexural frequency F will be inversely proportional to the size of bonding defect. According to this principle, an experienced operator can estimate the approximate size of void by listening to the impact sounds. Thus F can be automatically extracted to evaluate the approximate size of the defect, which is an important parameter for the NDT&E result assessment and maintenance planning. Relying on the combined information of F and quantitative bonding quality indicator such as R [6], it is possible to detect and evaluate the degree of debonding and the size of the defect quantitatively by only a single impact. Nonetheless, factors such as the shape of void, relative impact position, the multiple mode resonance frequencies as well as the background noise make it difficult to extract automatically the fundamental frequency F by classical threshold methods.

The classic threshold based clustering methods generates hard partitions, and in a partition, each pattern belongs to one and only one cluster. In reality, there is very often no sharp boundary between clusters. So, the fuzzy clustering method is often more suitable for practical applications. Membership degrees between zero and one are used in fuzzy pattern recognition instead of crisp assignments of the data to clusters [12]. This is the reason why experienced operators can often outperform traditional automatic algorithms in signal explanation and understanding. Therefore, imitating human reasoning processes can potentially improve the pattern recognition performance. In [12], Liu et al. applied fuzzy pattern recognition on grinding burn damage monitoring based on acoustic emission (AE) features to improve accuracy. Wu et al. [13] proposed a fuzzy logic expert system for AE fault diagnosis of scooter platform. In this study, the application of fuzzy theory for defect assessment of tile–walls is presented. The objective of the proposed method is to mimic human expert with a fuzzy system in order to automate the fundamental-frequency extraction for void size estimation. In order to realize this task, impact sound signals received by a microphone are used for the determination of bonding quality and also for the size assessment whenever a void is detected.

The paper is organized as follows. First, the theoretical basis of fuzzy analysis and size estimation is introduced. Next, the fuzzy-analysis-based feature extraction processing method including the design of membership functions and approximate-reasoning rules is outlined. Finally, experimental results of on-site tests and some discussions are presented to verify the proposed method.

2. Basis of fuzzy system [14,15]

In view of its ability to overcome the limitations of binary logic, the theory of fuzzy logic has drawn more and more attention in many fields such as control, automation and pattern recognition. Fuzzy logic is a useful approach to simplify a complex system in engineering application. Besides, fuzzy analysis can be applied to describe and process inexact and incomplete data, which is often encountered in real situations involved human behaviour. Hence, it is possible to apply fuzzy logic to represent the human knowledge and experience in the form of rule-based logic so that the decision output can be obtained. So the performance of this fuzzy analysis system will be superior to that of a simple classical 0–1 binary logic system.

The implementation of fuzzy analysis can be divided into 3 key stages: fuzzification of the input values, rule-based fuzzy reasoning and defuzzification for the system output.

The input variable is first converted into its fuzzy set domain, e.g., "very high", "high", "medium", "low" and "very low", each set with a defined "membership function". In contrast to the classical logic, which has only two crisp values expressed in the forms of "yes or no", "true or false" or "0 or 1", the concept of fuzzy logic is based on membership functions, which can take on arbitrary values from the interval [0,1]. The membership function describes the degree to which an object belongs to a certain set.

Fuzzy inference is the decision making process and the most important operation in fuzzy expert systems and fuzzy controllers. However, in a lot of engineering systems, data such as sensory readings are often in the form of crisp values. In order to allow the crisp values to be processed by the fuzzy inference engine, a fuzzification step is needed to convert crisp values into appreciate fuzzy sets. Similarly, as most of engineering systems cannot handle the fuzzy results produced by the fuzzy inference engine directly, a defuzzification step is needed to convert the fuzzy sets into crisp values which can be recognized and processed by the engineering systems. The knowledge and experience of the human expert are represented with rules such as:Rule 1: If $X_1 = A_{11}$ . . . and $X_i = A_{1i}$ . . . and $X_n = A_{1n}$,then $Y = B_1$ where X_i and Y are input and output of the system, A_{1i} is the fuzzy set which is mapped from the original input variable. B_1 is the fuzzy set in the output domain.

Finally, the defuzzification stage performs the conversion of a fuzzy set formed by approximate reasoning into a crisp value to produce the output. The latter is often defined as the abscissa of the center of gravity of the area under the membership function of the output fuzzy set.

3. Size assessment of defect

3.1. Theoretical basis

For the sake of convenience, a void-filled tile–wall is modeled as a thin rectangular plate with simply supported edges. Accord to vibration principles, the flexural vibration frequency of different modes can be written as [11]

$$f_{mn} = 0.453c_{L}h\left[\left(\frac{m+1}{L_x}\right)^2 + \left(\frac{n+1}{L_y}\right)^2\right] \tag{1}$$

where c_L is the velocity of longitudinal waves in an infinite plate, h is the thickness of plate, L_x and L_y are dimensions of rectangular plate, and m and n are integers (beginning with zero). From Eq. (1), the analytical expression for the fundamental frequency of flexural
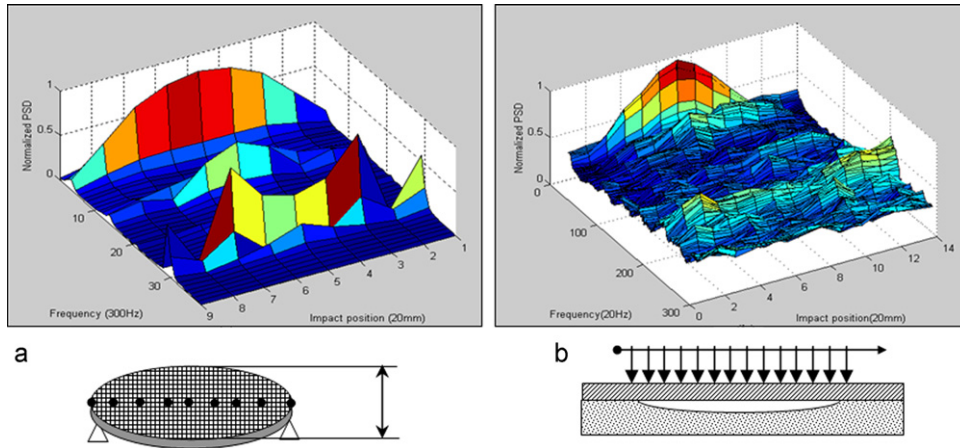
Fig. 1. Analysis and experimental result of fundamental frequency and impact position.

vibration of a thin plate is

$$F = f_{0,0} = 0.453 c_L h \left[\left(\frac{1}{L_x} \right)^2 + \left(\frac{1}{L_y} \right)^2 \right] \tag{2}$$

It can be seen that the fundamental frequency of flexural resonance F will increase with diminishing void size. Hence, F offers a possible indicator for the size assessment of tile–wall debonds.

Of course, because of the physically inhomogeneous material and complexity of the vibration process, the accuracy of size assessment based on F is relatively low. However, considering that the aim of void-size evaluation is just to provide an approximate reference for the maintenance planner and operator, the less accurate evaluation is already good enough in practical applications.

3.2. Difficulties in extraction of fundamental frequency

In practical extraction of F, for approximately the same size, the relative amplitude of fundamental-frequency peak will be affected by the shape of void and relative location of impact over the void. As a result, automatic determination of fundamental frequency will be difficult with traditional threshold operation.

Due to the difficulties in theoretical analysis of the relationship between sound radiation and impact position of void, finite element (FE) analyses (see Fig. 1(a)) are performed to investigate the effect of impact position on resulting sounds [7]. With the commercial package ANSYS 56, a harmonic analysis of a thin circular plate (with a diameter of 160 mm, thickness of 7 mm) impacted at different positions over a circular void is conducted. The assumed parameters of concrete are input in the FE model in order to simulate the tile–wall material. Results from FE numerical studies are presented as Fig. 1(a) in terms of the normalized spectra for 9 different impacts at points along a plate diameter. It is shown that the relative intensity of the fundamental component becomes stronger with the impact location getting nearer to the center of the void.

Correspondingly, the variation of different high-order components in impact sounds is investigated experimentally on a concrete specimen, which has an approximate-circle void with a diameter of about 200 mm. Experimental results are shown in Fig. 1(b), revealing that the fundamental flexural vibration component becomes apparently stronger when the impacting position moves closer to the center of the void. Impacts near the edge of the void create sounds with weak fundamental frequency. This agrees well with the trend obtained by FE analysis in Fig. 1(a).

In conclusion, it is observed that impact near the center of the void leads to a strong fundamental-frequency peak that is easy to be extracted. On the other hand, a weak fundamental-frequency

peak with strong multiple mode frequency peak caused by impact near the edge of the void will make the automatic extraction difficult. Thus the performance of size assessment will be seriously affected.

In this paper, guided by the superior evaluation ability of the experienced human operator, fuzzy technique is adopted to deal with difficulties in defect assessment.

4. Generation of fuzzy logic model

4.1. Basis for fuzzy assessment

Relying simply on threshold detection, the reliability and precision of fundamental-frequency extraction will deteriorate when the amplitude of the F peak is weaker than fake peaks caused by noise or multiple-mode resonance. Due to the imprecise characteristics of the problem, it is difficult to find binary-logic judgment rules to identify the F peak out of the many peaks existed in the sound signals. With fuzzy analysis, human understanding of the fundamental frequency and interference effects based on parameters such as the amplitude and width of peak, the shape characteristics of spectrum and the information from neighboring impact can be jointly used to obtain the results of improved precision.

Before the corresponding fuzzy algorithm is developed, we shall examine the features of the impact sound which enable the F extraction task to be accomplished by the experienced operator:

Firstly, as mentioned before, a high relative amplitude of any frequency peak implies the high possibility of the presence of F. This peak value is defined as X_1.

The relative strength of the band lower than the assumed fundamental frequency can also offer an indicator for detection; this indicator is defined as X_2. Generally, X_2 should be a low value.

In addition, impact sounds for neighboring points scanned on the wall can also provide reference information for judging whether there is a big void. The cross-correlation coefficient of corresponding parts of the power spectral density (PSD) of two consecutive impact sounds is defined as X_3.

To enhance the performance of fuzzy inference engine, one more indicator is introduced. The original PSD is first filtered by a 4th-order filter. From the intersection between the original and filtered PSD, cross-points are obtained (see Fig. 2 where many peaks are observed). Both the amplitude and the width of each peak are measured. The width is defined using the cross-points. The ratio of width to amplitude of each frequency peak, defined as X_4, can be used as one of the indictors for judgment. A peak with extremely
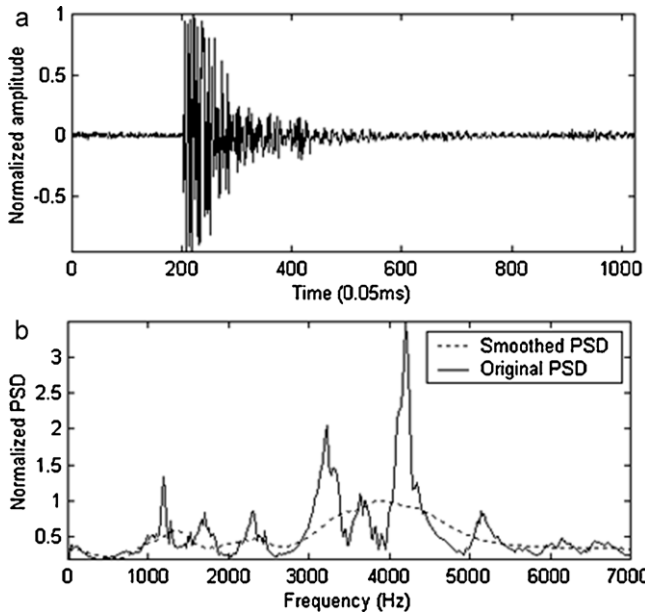
Fig. 4. Membership function of system output.

Fig. 2. Waveform and corresponding original and smoothed PSD of impact sound.

defined as shown in Fig. 3, which are used to convert each crisp input into appropriate fuzzy sets. Curves in Fig. 3(a)–(d) represent the process for calculating the degree of confidence for X_1, X_2, X_3 and X_4 respectively. The membership functions in Fig. 3(a)–(c) exhibit similar pattern, with the small value of input indicating low possibility of fundamental frequency and large value of input corresponding to high possibility. In Fig. 4(d), as both inputs, with extremely large or small value, are less likely to be judged as fundamental spectral peak. The 'Medium' case, on the other hand, implies a high possibility of the presence of F.

wide or narrow width is less likely to be judged as the F peak corresponding to the fundamental frequency.

The above four indicators derived from the impact sound will act as inputs to the fuzzy logic model. To avoid the adverse influence caused by abnormal impacts, the quality factor of the received signal is obtained first by estimating the signal/noise ratio (SNR) to guarantee the effectiveness of algorithm.

4.2. Fuzzification process for model inputs

In the fuzzification stage, the inputs X_1, X_2, X_3 and X_4 of impact sounds will be extracted and converted to the appropriate fuzzy sets. The design of the membership function for each fuzzy set plays a crucial role in influencing the performance of the fuzzy system. In the present exercise, the definitions of membership functions are designed based on extensive experimental analyses of the relationship between the inputs and the corresponding defect case.

To get the inputs for the analysis, the PSD of impact sounds is subtracted by its smoothed counterpart to obtain the original line spectrum (see Fig. 2 for the details). Then the line spectral components including the fake ones and the one associated to the fundamental frequency are obtained by a direct threshold detection method. According to the characteristics of impact sounds and human experience, the membership functions for these inputs are
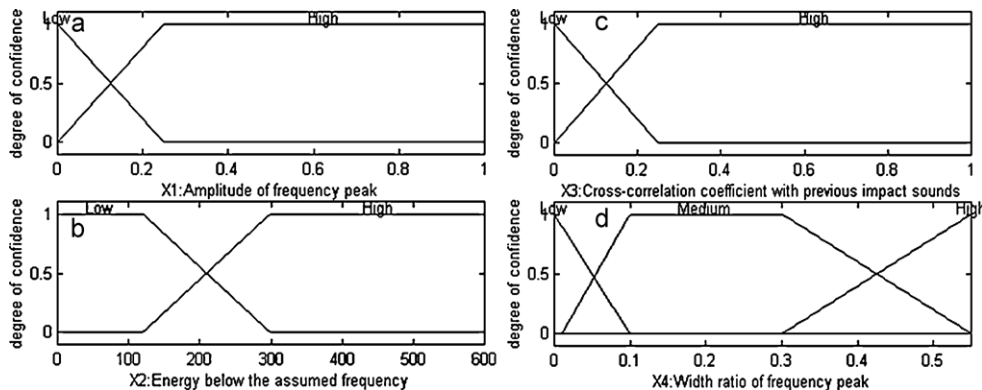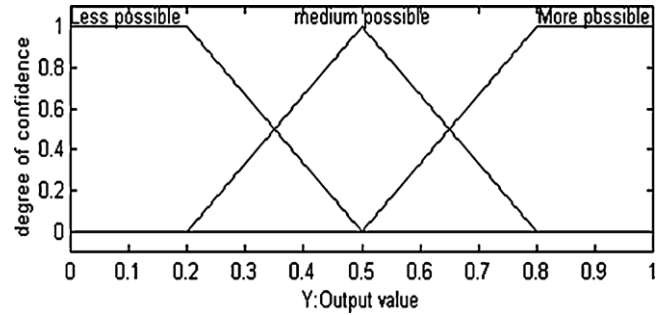
4.3. Fuzzy reasoning

Based on the experience and knowledge about the relationship between the inputs and the characteristics of defects mentioned in Section 4.1, the underlying knowledge rules and associated descriptions are presented as:

Rule 1: If X_1 = High and X_2 = Low and X_3 = High and X_4 = Medium, then Y = More possible
Rule 2: If X_1 = Low and X_2 = High and X_3 = Low and X_4 = High, then Y = Less possible
Rule 3: If X_1 = Low and X_2 = High and X_3 = Low and X_4 = Low, then Y = Less possible
Rule 4: If X_1 = Low and X_2 = Low and X_3 = High and X_4 = Low, then Y = Medium possible
Rule 5: If X_1 = Low and X_2 = Low and X_3 = High and X_4 = High, then Y = Medium possible
Rule 6: If X_1 = Low and X_2 = High and X_3 = High and X_4 = High, then Y = Less possible
Rule 7: If X_1 = Low and X_2 = High and X_3 = High and X_4 = Low, then Y = Less possible
Rule 8: If X_1 = High and X_2 = Low and X_3 = High and X_4 = Low, then Y = Medium possible

Fig. 3. Membership functions of 4 selected inputs.

Rule 9: If X_1 = High and X_2 = Low and X_3 = High and X_4 = High, then Y = Medium possible

Rule 10: If X_1 = High and X_2 = High and X_3 = High and X_4 = Medium, then Y = Medium possible

Rule 11: If X_1 = High and X_2 = Low and X_3 = Low and X_4 = Medium, then Y = Medium possible

Rule 12: If X_1 = High and X_2 = High and X_3 = Low, then Y = Less possible

These fuzzy rules are designed based on typical patterns of fundamental spectral peaks, as well as typical interferences leading to misdetection or failure in detecting fundamental spectral peaks. To be specific, Rule 1 corresponds to the spectral peak with distinct features of fundamental frequency in all four inputs. Thus the presence of 'High' X_1, 'Low' X_2, 'High' X_3 and 'Medium' X_4 indicates a high likelihood of being *F*. On the other hand, Rules 2, 3, 6, 7 and 12 are presented to define the cases with pretty low possibility of being fundamental spectral peaks. For example, Rules 2 and 3 represent typical features of non-fundamental frequency in all four inputs. Rules 6, 7 and 12 are proposed to eliminate misdetection of *F* caused by certain interferences which leading to one *F* type feature in four inputs. Meanwhile, for cases with two or three inputs exhibiting fundamental spectral peak pattern, medium likelihood of being *F* is assigned, as indicated in Rules 4, 5, 8, 9, 10 and 11. The output membership functions are shown in Fig. 4.

4.4. Defuzzification

In the defuzzification stage, the output fuzzy set is obtained by rule-based reasoning and mapped to an output membership function against *Y* (which is not plotted in Fig. 4 as this depends on the combined inputs in each case).

After defuzzification, the particular frequency is recognized as a fundamental frequency *F* with a confidence degree obtained (indicated in Fig. 6 by a circle). A final threshold will be set to determine whether this output confirms the acceptance of the frequency under test as *F* or not.

5. Experimental study

5.1. Set-up for NDT experiments

The proposed NDT&E experimental system is illustrated in Fig. 5. The apparatus adopted includes: a steel sphere of diameter 23 mm driven by a linear solenoid actuator; a pre-amplifier
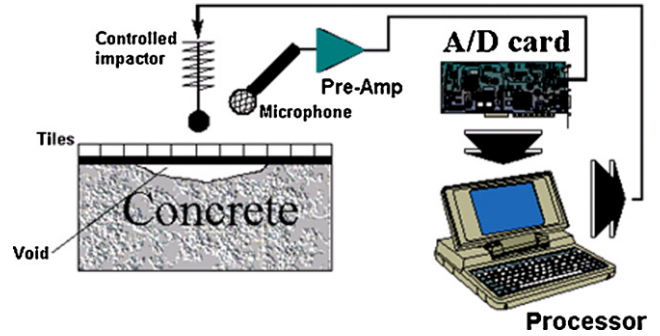

Fig. 5. Schematic of NDT experiment set-up.

module; an A/D converter card with 40 kHz sampling rate; a highly directional microphone. Such an impacting system provides a simple mechanism to produce tapping actions for generating impact sounds for defect detection. An NDT&E module developed from this experimental system is installed on an automated scanning device, which is incorporated into a climbing robot [1,2], to perform health monitoring of the tiles on the building; the NDT&E module, the automated scanning device and the climbing robot are integrated together to form an automated solution with high safety for tile–wall inspection.

The main advantage of this impact inspection method is that the impacting device and microphone need not be coupled through the surface of the wall. This is of great convenience for the robot system working at heights. Moreover, it will take less time and effort to perform inspection on large area of tile–walls.

5.2. Experimental results

Experiments on a tile–wall in the campus of City University of Hong Kong are carried out to demonstrate the effectiveness of the present method. For easier reference, the fundamental frequencies extracted by the method are marked by circles on vertical poles in Fig. 6 with their pole heights reflecting the output confidence degree. As seen from Fig. 6(a), (c) and (d), fundamental frequencies even with relatively weak amplitudes can be correctly obtained by overcoming the influence of the relatively strong multiple-mode frequency peaks. In Fig. 6(b), a peak picked out from the multiple-mode frequency peaks is not regarded as *F* because of the low confidence degree obtained after going through the fuzzy reasoning process (0.48).
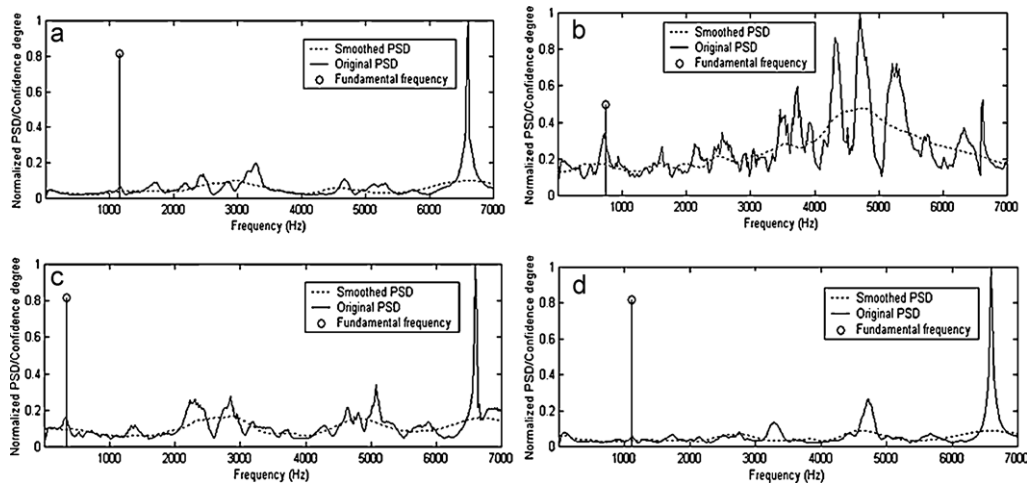

Fig. 6. Frequency extracted and corresponding confidence degree obtained.
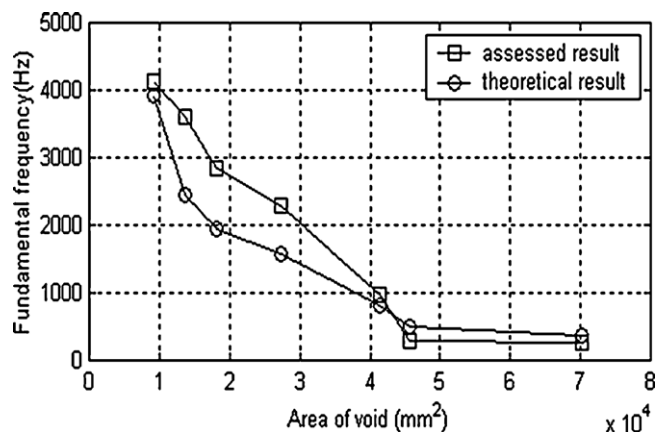
Fig. 7. Experimental results of fuzzy based defect assessment.

In Fig. 7, the results of fundamental-frequency extraction are summarized with the corresponding estimated size of the void. At the same time, the actual physical sizes of debonding are plotted to verify the relative effectiveness of the proposed method. As shown in Fig. 7, the basic agreement of the fundamental frequency F obtained from fuzzy assessment and theoretical calculation indicated that the fuzzy-system-based method introduced in this paper performs well for practical implementation.

6. Conclusion

To improve the efficiency and performance of the robotic wall-inspection system, a fuzzy-logic-based fundamental-frequency extraction algorithm has been developed to overcome the difficulties in void-size estimation based on impact sounds. With the employment of human knowledge, multiple features of impact sound are used as the inputs for a rule-based fuzzy-logic model system for obtaining the fundamental frequency F for automatic NDT&E use. Site experimental results obtained in university-campus have been reported and have demonstrated the relative effectiveness of the described method.

Acknowledgement

References

[1] B.L. Luk, K.P. Liu, Z.D. Jiang, F. Tong, Robotic impact-acoustics system for tile–wall bonding integrity inspection, Mechatronics 19 (2009) 1251–1260.
[2] S.K. Tso, F. Tong, Robot assisted wall inspection for improved maintenance of high-rise buildings, in: Proceeding of the 20th International Symposium on Automation and Robotics in Construction, September 21–24, 2003, Eindhoven, Netherlands, 2003.
[3] T. Ito, T. Uomoto, Nondestructive testing method of concrete using impact acoustics, NDT&E International 30 (1997) 217–222.
[4] K. Mori, A. Spagnoli, A new non-contacting non-destructive testing method for defect detection in concrete, NDT&E International 35 (2002) 399–406.
[5] M. Asano, T. Kamada, M. Kunieda, K. Rokugo, Impact acoustics methods for defect evaluation in concrete, in: Proceedings of Nondestructive testing-civil engineering 2003 (NDT-CE2003), 2003, http://www.ndt.net/article/ndtce03/papers/v040/v040.htm.
[6] K.P. Liu, B.L. Luk, T.W. Yeung, S.K. Tso, F. Tong, Wall inspection system for safety maintenance of high-rise buildings, Special Issue of International Journal of Performability Engineering 3 (2007) 187–197.
[7] F. Tong, S.K. Tso, X.M. Xu, Tile–wall bonding integrity inspection based on time-domain features of impact acoustics, Sensors and Actuators A: Physical 132 (2006) 557–566.
[8] F. Tong, S.K. Tso, M.Y.Y. Hung, Impact-acoustics-based health monitoring of tile–wall bonding integrity using principal component analysis, Journal of Sound and Vibration 294 (2006) 329–340.
[9] F. Tong, X.M. Xu, B.L. Luk, K.P. Liu, Evaluation of tile–wall bonding integrity based on impact acoustics and support vector machine, Sensors and Actuators A: Physical 144 (2008) 97–104.
[10] B.L. Luk, K.P. Liu, F. Tong, K.F. Man, Impact-acoustics inspection of tile–wall bonding integrity via wavelet transform and hidden Markov models, Journal of Sound and Vibration 329 (2010) 1954–1967.
[11] T.D. Rossing, N.H. Fletcher, Principles of Vibration and Sound, Springer-Verlag, New York, 1994.
[12] Q. Liu, X. Chen, N. Ginday, Fuzzy pattern recognition of AE signals for grinding burn, International Journal of Machine Tools & Manufacture 45 (2005) 811–818.
[13] J.D. Wu, Y.H. Wang, M.R. Bai, Development of an expert system for fault diagnosis in scooter engine platform using fuzzy-logic inference, Expert Systems with Applications 33 (2007) 1063–1075.
[14] Anton Kummert, Atlas Elektronik GmbH, Fuzzy technology implemented in sonar system, http://www.fuzzytech.com/e_a_kumm.htm.
[15] M. Hanss, S. Hurlebaus, L. Gaul, Fuzzy sensitivity analysis for the identification of material properties of orthotropic plates from natural frequencies, Mechanical Systems and Signal Processing 16 (2002) 769–784.

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