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Evaluation of tile–wall bonding integrity based on impact acoustics and support vector machine

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Abstract

It is well recognized that the impact-acoustic emissions contain information that can indicate the presence of the adhesive defects in the bonding structures. In our previous papers, artificial neural network (ANN) was adopted to assess the bonding integrity of the tile–walls with the feature extracted from the power spectral density (PSD) of the impact-acoustic signals acting as the input of classifier. However, in addition to the inconvenience posed by the general drawbacks such as long training time and large number of training samples needed, the performance of the classic ANN classifier is deteriorated by the similar spectral characteristics between different bonding status caused by abnormal impacts. In this paper our previous works was developed by the employment of the least-squares support vector machine (LS-SVM) classifier instead of the ANN to derive a bonding integrity recognition approach with better reliability and enhanced immunity to surface roughness. With the help of the specially designed artificial sample slabs, experiments results obtained with the proposed method are provided and compared with that using the ANN classifier, demonstrating the effectiveness of the present strategy.

Keywords: Support vector machine; Impact acoustics; Nondestructive inspection; Classification

1. Introduction

With the extensive adoption of tiles on external walls of high-rise buildings for the purpose of decoration and wall protection in metropolitans like Hong Kong, there is unfortunately an increasing number of accidents caused by tiles dropping due to adhesive failure or bonding defects [1–3]. In response to the need for automatic maintenance of external walls of high-rise buildings, an impact-acoustics method based on a novel high-safety tile–wall inspection robotic system [4] has been developed in our previous works [5–7] which is further extended in this paper.

The well recognized fact that if bonded structures are impacted with a small, hard object, the characteristics of sounds emanated will vary depending on the bond quality lays the original basis for the development of the impact-acoustic method in bonding quality evaluation. Avoiding the need to glue the sensor on the test object, the manual operation of this method is simple, convenient and cheap, but is unfortunately subjective and operator-dependent. To remove its dependence on the human ear and experience, there have appeared many efforts to automate the impact test operation to develop a quantitative, convenient, easy-use and cost-efficient nondestructive method for disbonds characterization.

Based on the experimental results and FEM analysis, Ito [8] pointed out that the degradation of stiffness of concrete structure can be evaluated with the resonant frequencies of the impact acoustics. Masanori Asano [9] derived from the frequency distribution impact acoustics parameters for developing a spectral feature-based defects detection system. In another frequency-distribution-based investigation [10], Huadong Wu defined the ratio of the power of the lower 1/3 frequency range to that of the overall frequency range in the impact-sounds spectrum as

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the *power accumulation ratio factor* and used it to characterize the integrity of multi-layered materials. Pearson [11] developed an impact acoustics-based nondestructive system to detect the integrity of wheat kernels using time-domain and spectral modeling of signal. In a similar investigation reported by Liu [4], a parameter calculated by the area of different band in the power spectrum density (PSD) of the impact-acoustic signals is defined as the *sound intensity ratio* to quantitatively identify the bonding defects of the tile–wall. Based on the theoretical analysis of the impact dynamics, Tong [5–7] proposed tile–wall bonding state monitoring methods which employ the artificial neural network (ANN) classifier with features extracted from the PSD or time domain pattern of the impact-acoustic signals.

As a convenient and traditional approach to fault detection and diagnosis, threshold (limit) checking method is widely adopted in the previous research [4,8–11] to discriminate the impact-acoustic signals. However, the performance of the threshold judging method is sensitive to the optimal selection of the threshold which poses serious difficulties in the practical applications. In our previous works, ANN classifier was also applied to classify the features extracted from the impact-acoustic signals into different bonding classes [5–7]. Nonetheless, as a typically machine learning (ML) classifier, the ANN methods are based on the empirical risk minimisation (ERM) principle [12], which has been recognized as cannot always minimise the actual risk. Meanwhile, the effectiveness of the ANN methods is closely related to the amount of training samples. Vapnik [13] found that two correlated factors might lead to the classification error: insufficient training sample and unreasonable structure. As to the impact-acoustics based tile–wall bonding integrity inspection applications herein, both problems are rather common.

Moreover, limitations in impact-acoustic signal features also considerably affect the generalization ability of the ANN classifier. As our previous research [6,7] revealed, the features directly obtained from the signature spectra are found to be sensitive to the surface irregularities of the target surface, as the interaction between the impactor and the target surface in a nominally single tap would lead to overlapping patterns between different bonding integrity. As a result, the actual assessment performance of the ANN classifier based on the frequency-domain feature was deteriorated. So far, some feature-related attempts employing time-domain features [6] or the statistics transform of spectral features [7] have been conducted upon this problem in our previous work, the work of this paper will focus on the adoption of alternative classifier.

Founded on powerful statistical learning theory, the support vector machine (SVM) invented by Vapnik in 1979 is characterized as its ability of studying the properties of learning procedure in a small size sample case, and thus provided a new solution for solving these problems. Recently, the application of SVM [14–18] is gaining more and more attention in the fields of pattern recognition and classification motivated by its two distinct features [14], i.e., first, it is often associated to the physical meaning of the data and hence easy to interpret (in contrast, ANN does not contain any physical meaning). Second, it requires only small amount of training samples.

In this paper, based on signal modeling and analysis in our previous research, SVM is introduced to statistically model the impact-acoustic signals via the spectral features to derive a robust approach for the tile–wall bonding integrity assessment at the presence of the abnormal impacts caused by surface irregularities. To validate the effectiveness of the proposed method, the classification results achieved with impact-acoustic signals experimentally obtained on the prepared sample slabs using present method are compared with that via the classic ANN classifier.

2. Basis of SVM

2.1. Basis of SVM [14–18]

Because the theory of SVM has been systematically presented in many literatures, its concept is only briefly introduced in this section. The basic idea of SVM is to transform the signal to a higher dimensional feature space and find the optimal hyperplane in the space that maximises the margin between the classes. Briefly, given a set of N data points $\{x_i, y_i\}_{i=1}^{N}$, where $x_i \in \mathbb{R}^n$ is the i-th input data, and $y_i \in \{-1,+1\}$ is the label of the data. The SVM approach aims at finding a classifier of form:

$$y(x) = \mathrm{sign}\left[\sum_{i=1}^{N} \alpha_i y_i K(x_i, x) + b\right] \tag{1}$$

where α_i are positive real constants and b is a real constant, in general, $K(x_i,x) = \langle\phi(x_i),\phi(x)\rangle$, $\langle\cdot,\cdot\rangle$ is inner product, and $\phi(x)$ is the nonlinear map from original space to the high dimensional space.

In the high dimensional space, we assume the data can be separated by a linear hyperplane, this will cause:

$$y_i[w^T\phi(x_i) + b] \geq 1, \quad i = 1, \ldots, N. \tag{2}$$

In case of such separating hyperplane does not exist, we introduce a so called slack variable ξ_i such that

$$\begin{cases} y_i[w^T\phi(x_i) + b] \geq 1 - \xi_i, & i = 1, \ldots, N \\ \xi_i \geq 0, & i = 1, \ldots, N \end{cases}. \tag{3}$$

According to the structural risk minimization principle, the risk bound is minimized by the following minimization problem:

$$\min_{w,b,\xi} \; J_1(w, b, \xi) = \frac{1}{2}w^T w + C\sum_{i=1}^{N}\xi_i \tag{4}$$

where C is a positive constant parameter used to control the tradeoff between the training error and the margin.

2.2. LS-SVM

Least squares support vector machines (LS-SVM) [16,17] is a variant of SVM, which employs least squares error in the training error function. Here we introduce an LS-SVM classifier by reformulating the minimization problem (4) as:

$$\min_{w,b,e} J_2(w,b,e) = \frac{1}{2}w^T w + \frac{\zeta}{2}\sum_{i=1}^{N} e_{c,i}^2. \tag{6}$$

Subject to the equality constraints:

$$y_i[w^T \phi(x_i) + b] = 1 - e_{c,i}, \quad i = 1, \ldots, N \tag{7}$$

where ζ is a constant. The least square SVM (LS-SVM) classifier formulation above implicitly corresponds to a regression interpretation with binary targets $y_i = \pm 1$.

In this study, w and b were calculated using a Matlab toolbox, LS-SVMlab1.5 developed by Suykens and Vandewalle [18].

3. Experimental results

3.1. Experimental configuration

In this section, experiments are carried out on artificial sample slabs to investigate the practical characteristics of the impact-acoustics signature. To simulate the physical bonding status, 3 types of sample slabs are prepared. One is a tiled-concrete slab of good bonding strength (called Solid1 class); the second type of tiled-slab contains a Ø140 mm circle-shaped void at concrete substrate layer at the center location (called void class).

When considering the simplified impact mode, the influence of the target surface roughness on the resulting acoustic signature is ignored. However, it has been observed that the abnormal multiple contacting behaviors caused by the surface irregularity greatly affect the actual acoustic characteristics [6,7]. So the third type of samples slab is specially prepared to feature good bonding integrity and rough surface formed by edges of tiles (called Solid2 class). The dimensions of all the slabs are: 400 mm × 400 mm × 150 mm.

The NDT experimental system is illustrated in Fig. 1. The apparatus adopted includes: a rigid steel sphere of diameter 12 mm pushed by a coil used as the controlled impactor; a pre-amplifier module; an A/D converter card with 40 kHz sampling rate; a highly directional microphone. Such an impacting system generates a well-defined and simple input which in turn excites impact sounds with characteristics that facilitate signal interpretation.

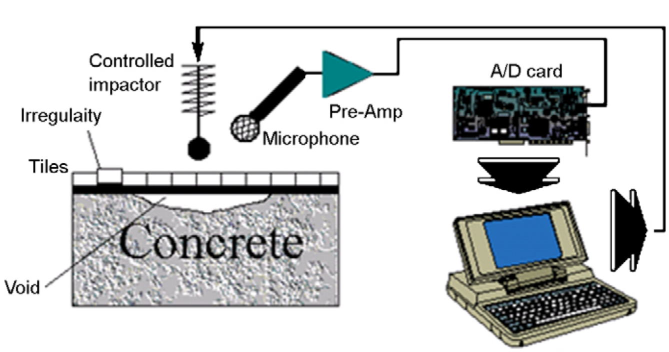

Fig. 1. Experimental setup.

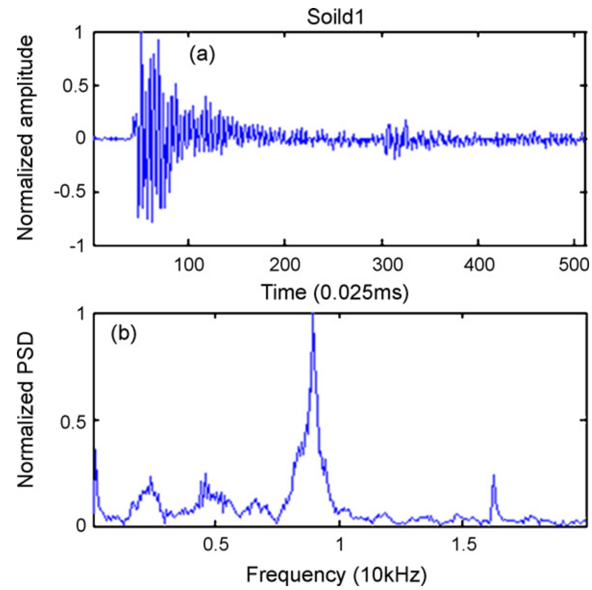

Fig. 2. Time history (a) and PSD (b) of typical impact sound from Solid1 class slab.

3.2. Signature obtained and analysis

In time-domain, each time history contains 512 signal points sampled at 40 kHz, triggered by the pulse used to activate the impactor. To obtain the frequency-domain information, the power spectral density (PSD) of the signature is obtained with the 512-point fast Fourier transform (FFT) calculation based on the original time history. To remove the influence of impact strength, the resulting PSD is then normalized with its maximal magnitude to get the normalized PSD.

The typical signals obtained experimentally are illustrated in Figs. 2–4. From the resulting PSD curves (see Figs. 2(b), 3(b) and 4(b)), a ring peak located around 8–10 kHz

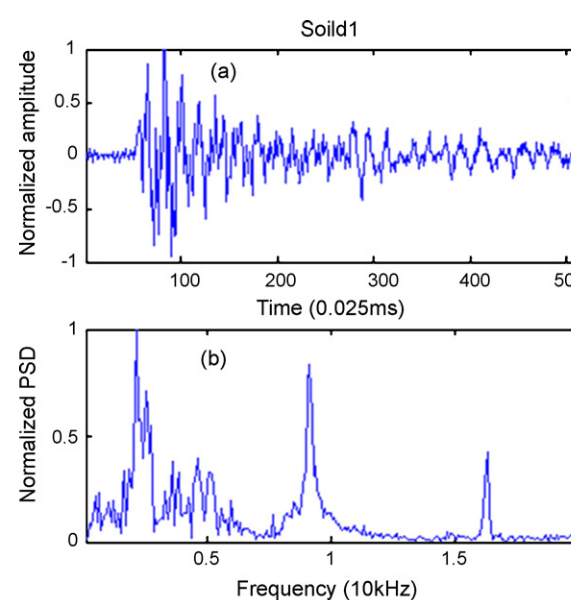

Fig. 3. Time history (a) and PSD (b) of typical impact sound from Solid2 class slab.

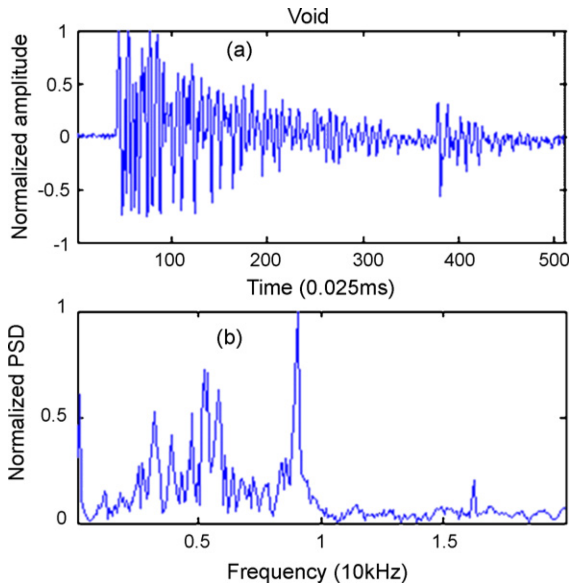

Fig. 4. Time history (a) and PSD (b) of typical impact sound from void class slab.

is observed, which corresponding to the steel sphere's ringing as pointed out by [11–12]. Meanwhile the spectral components within 0–8 kHz are concluded to be associated with target structure's multiple mode flexural vibration [6]. According to previous analysis [11,12], the energy distribution of these two components may indicate the presence of bonding defects, which provides a theoretical basis for the classic spectral method. As shown in Figs. 2(b) and 4(b), for Solid1 and void class, the relative strength of these two components of impact sounds is in good agreement with previous theoretical assessment [11,12], with the steel sphere's spectral component reigning in Fig. 2(b) and the 0–8 kHz component dominating (see Fig. 4(b)) respectively.

However, for Solid2 class characterized as good bonding integrity but with surface irregularities, tapping on the rough surface leads to multiple interactions between impactor and the target surface in a nominally single tap [9,11,12]. Due to the multiple contacts caused, the resulting time history contained multiple acceleration peaks and relatively weak ringing component (see Fig. 3(a)). As a result, the corresponding PSD curve exhibits patterns similar to that of the debonded cases (see Fig. 4(b)) in the corresponding frequency ranges.

The experimental analysis above shows that, in view of the normal impact, the pattern of PSD curve can clearly indicate the existence of bonding defects and may produce a feasible indicator for inspection and classification as reported by previous works [5–7]. However, as our previous investigation indicated [5–7], the abnormal taps caused by surface irregularities will impose difficulties on the ANN classifier in bonding property assessment due to the resulting similar spectral pattern between different classes.

It has been concluded that the main difference between ANNs and SVMs is in their risk minimisation [15]. In the case of SVMs, structural risk minimisation principle is used to minimise an upper bound based on an expected risk. Whereas in ANNs, traditional empirical risk minimisation is used to minimise the error in training of data. Thus the difference in risk minimisation may lead to a better generalisation performance for SVMs than ANNs. In the present paper, enlightened by the superiority of the SVM in pattern recognition and classification, the LS-SVM classifier is proposed to facilitate the robust assessment of tile–wall bonding integrity at the presence of the surface irregularities instead of the ANN.

4. Recognition via the proposed method

4.1. Multiple class classification

Regarding the tile–wall bonding integrity assessment system herein, there are three types of classes that need to be discriminated, 'Solid1', 'Solid2' and 'Void' class. Because SVM type classifiers can deal with only two classes, it is necessary to decompose a multiclass problem into a set of binary problems, and then combine to make a final multiclass prediction.

The basic idea behind combining binary classifiers is to decompose the multiclass problem into a set of easier and more accessible binary problems. Standard modern approaches for combining binary classifiers can be stated in terms of what is called output coding [19]. The basic idea behind output coding is the following: given k classifiers trained on various partitions of the classes, a new example is mapped into an output vector. Each element in the output vector is the output from one of the k classifiers, and a codebook is then used to map from this vector to the class label. Regarding the three classes impact-acoustic signals, three classifiers are designed, among which the first classifier is trained to discriminate classes Solid2 and Void from Solid, the second classifier is trained to discriminate classes Solid1 and Void from Solid2, and the third classifier is trained to discriminate classes Solid1 and Solid2 from Void. In the present work, one-versus-all (OVA) output coding scheme [18] contained in the LS-SVMlab toolbox was used for the multiple class applications as shown in Fig. 5.

4.2. Feature extraction and SVM recognition

The LS-SVM based recognition generally consists of the training and classification. Data set are firstly trained with LS-SVM respectively through training sets obtained from the corresponding artificial slabs. The whole PSD of the impact sounds was divided into 16 equal intervals, and the area of each was extracted as the feature to be used as the input of the LS-SVM classifier. In the training stage implemented using the LS-SVMlab [18], the fast conjugate gradient algorithm is adopted to solve the set of linear equations [20] with the Radial basis function (RBF) kernel selected as the kernel scheme. After the training procedure, the LS-SVM classifier is tested with the test set. To illustrate the advantages of LS-SVM methodology, the results are compared with that obtained from a three-layer BP artificial neural network consisting of a 16-node input layer, 8-node hidden layer as well as a two-node output layer.

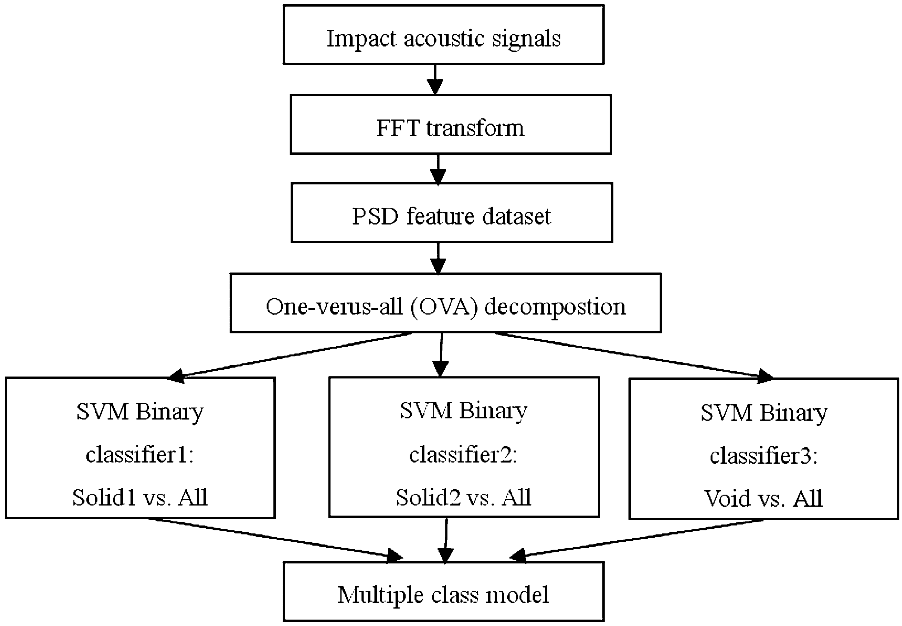

Fig. 5. Multiple class methodology using OVA approach.

4.3. Classification results

In this study, impact sounds obtained in the laboratory with 3 typical sample specimens mentioned above are firstly divided into a training set and a test set. The training set of the sample data is used to train the LS-SVM model and the trained model is evaluated with the test set exclusively. In the overall 300 samples of samples for each bonding case, the initial training set contains 100 samples of Solid1, 100 samples of Solid2 and 100 samples of debonded signatures. The test set contains the remained 200 samples for each class. In the training process, the training set is randomly selected to provide enough information for the learning algorithm. For the aim of comparison, the training set is also applied to a classic frequency-domain feature-based ANN classifier. The classification results obtained with the proposed LS-SVM classifier and the ANN classifier are presented in Tables 1 and 2, respectively. To account for the effect of the random factor in simulation experiment, the simulation is independently carried out for 100 times to obtain the mean output adopted as the final result.

First, the influence of the surface roughness on the classification performance is considered. As shown in the upper half of Table 1, with LS-SVM classifier using the feature vectors extracted from PSD curve, the accuracy rate is 96.78 and 99.35% for Solid1 and Solid2 classes, 97.08% for the debonded case, indicating the good discriminating ability of the proposed approach with respect to bonding property and surface roughness. Utilizing the classic BP-ANN classifier, the classification rate of the Solid1, Solid2 and void class is 91.74, 94.27 and 95.95%, respectively for the test set (see the upper half of Table 2), implying performance degradation of the classifier caused by the surface irregularity induced similar patterns among different bonding qualities. Regarding the failure classification case where the solid classes are identified as void ones, the LS-SVM approach produces a false detection rate of 3.22 and 0.04% for Solid1 and Solid2 class, respectively, outperforming the BP-ANN counterpart associated with a false detection rate of 8.26 and 1.14%.

In addition, to make a comprehensive comparison between the proposed SVM approach and the conventional BP-ANN, classifications are also performed with larger training set, which consisting of 200 number of samples for each class, with the remained 100 samples each case composing the smaller test set. The performance of the two techniques based on bigger training

Table 1
Classification results with proposed LS-SVM method

Type	Training and testing setting	Mean training time (s)	Mean classification rate		
			Solid1	Solid2	Void
Solid1			96.78%	0	3.22%
Solid2	100 training samples 200 test samples	1.5930	0.61%	99.35%	0.04%
Void			0.49%	2.43%	97.08%
Solid1			99.03%	0	0.97%
Solid2	200 training samples 100 test samples	8.1210	0.21%	99.68%	0.11%
Void			0.74%	1.54%	97.72%

Table 2
Classification results of BP-ANN classifier

Type	Training and testing setting	Mean training time (s)	Mean classification rate		
			Solid1	Solid2	Void
Solid1			91.74%	0	8.26%
Solid2	100 training samples 200 test samples	39.2615	4.59%	94.27%	1.14%
Void			0.03%	4.02%	95.95%
Solid1			96.18%	0	3.82%
Solid2	200 training samples 100 test samples	45.7433	2.54%	96.90%	0.56%
Void			0.39%	3.22%	96.39%

set is provided in the bottom of Tables 1 and 2, respectively. It can be observed that, under a larger training set, SVM classifier still achieves superior performance compared to BP-ANN strategy. As indicated in the low half of Table 1, for SVM method, bigger training set leads to improvement of inspection performance, with the classification rate of Solid1, Solid2 and void increasing to 99.03, 99.68 and 97.72%, respectively. Similarly, bigger training set pulls the classification rate of the BP-ANN classifier to 96.18, 96.90 and 96.39%, respectively, which indicates bigger performance rise compared to that of SVM (see low half of Table 2).

Meanwhile, the training time of the two classifiers is also compared with the same simulation software (MATLAB) and hardware configuration. The comparison result is also shown in Tables 1 and 2 with the training of BP-ANN occupying 39.2615 s under 100 training samples and 45.7433 s under 200 training samples, that of the LS-SVM classier consuming only 1.5930 and 8.1210 s, respectively. It reveals that, using small and big

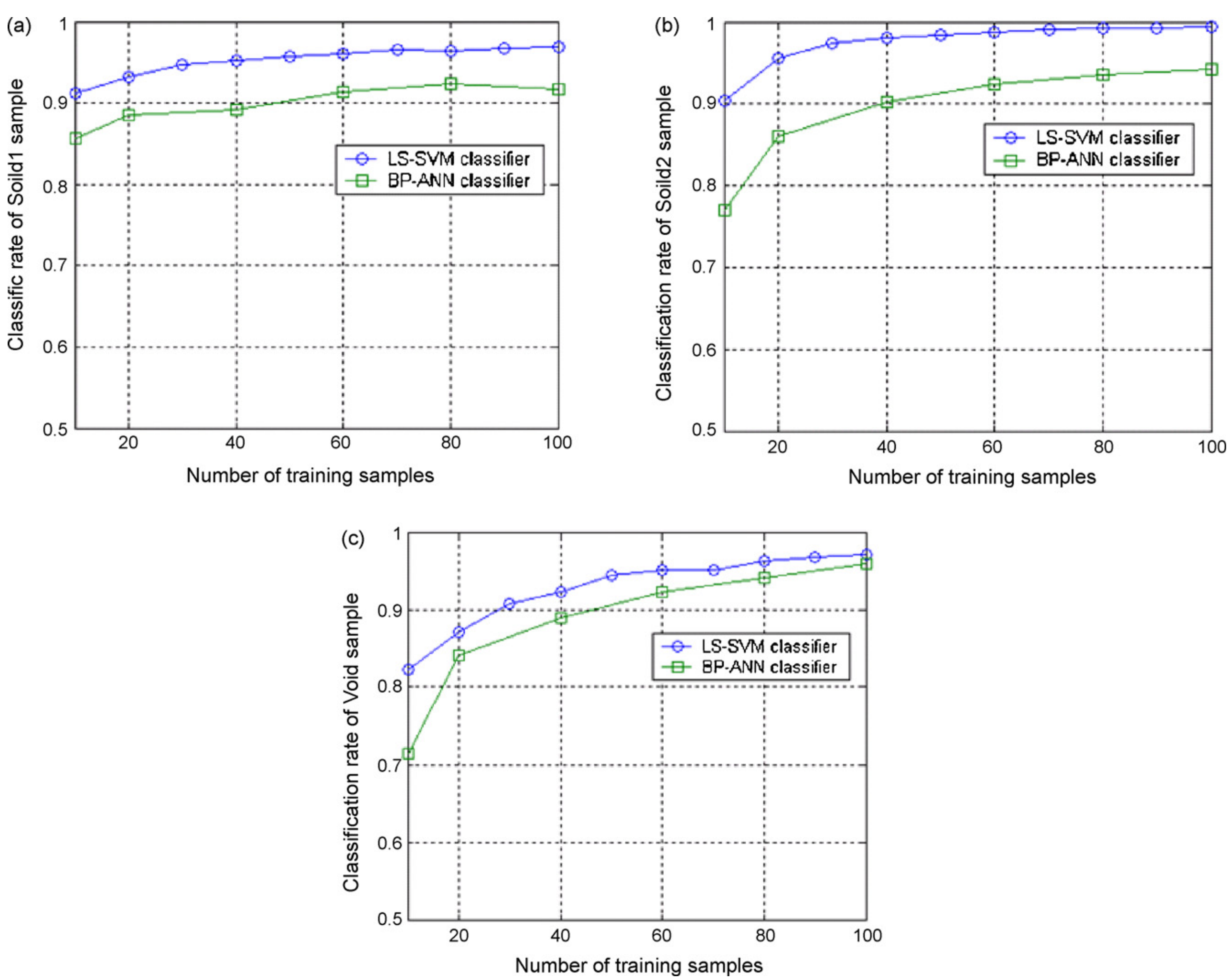

Fig. 6. Classification result against the number of training samples.

training set, the training of the BP-ANN classifier takes about 25 and 5.6 times more time than the SVM counterpart does respectively, implying more training time saving of SVM technique with respect to the BP-ANN under smaller training set.

To investigate the impact of the number of training samples on the classification result, experiments with different number of training dataset are carried out. The accuracy rates with respect to the number of training dataset obtained with the proposed LS-SVM approach and the BP-ANN classifier are shown in Fig. 6(a)–(c). It can be observed from the figures that the LS-SVM classifier generally exhibits better tolerance on the diminishing of the training set, with the accuracy rate of Solid1, Solid2 and void class standing at 92.03, 91.80 and 82.30%, respectively at only 10 training samples. For the ANN case, the classification rate is found to be significant affected by the number of training set, with the accuracy rate associated with 10 train samples greatly falling to 85.68, 78.20 and 71.40%, respectively for the Solid1, Solid2 and void class. The bigger degradation of the ANN performance, especially for Solid2 and void case, demonstrates the better generalization performance of the SVM model, which is also consistent with that concluded in [14].

5. Conclusion and discussion

Impact acoustics-based methods have been extensively investigated in the bonding integrity inspection of the layered adhesive structure. Most of our previous research employed the classic ANN classifier, the performance of which is found to be hindered by some drawbacks, such as time consuming training process, large amount of training dataset as well as the sensitivity to the feature mismatch caused by the abnormal impacts on surface irregularities.

Aiming to enhance the reliability with respect to the surface roughness, a novel NDE strategy based on the LS-SVM classifier is derived to develop a quantitative automatic tile–wall inspection with better reliability. Classification experiments carried out with the help of artificial slabs demonstrate that, while the existence of the surface non-uniformity seriously deteriorate the performance of the classic BP-ANN classifier, the proposed LS-SVM strategy exhibits high tolerance to the mismatch caused.

Moreover, classification experiments with different number of training dataset indicated that, the training dataset required to ensure satisfactory performance for the LS-SVM classifier is significantly fewer than that related with BP-ANN classifier. Meanwhile, another advantage of the LS-SVM approach is that the training time it needs is much shorter than that of the BP-ANN classier, mainly due to the fact that its training only depends on the support vectors, not on the whole train dataset as with ANN. These two superiorities of the LS-SVM classifier will be important for the practical implementation of the on-line inspection system that needs to deal with large amount of impact-acoustic signals. In view of the enhanced surface roughness immunity as well as the implementation convenience offered by the adoption of the SVM model, the proposed NDE method provides an efficient alternative for the impact-acoustic inspection of tile–wall bonding integrity.

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