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AN INTELLIGENT TAP TEST AS AN INSPECTION TOOL FOR CORROSION IN CHEQUER PLATE FLOORS

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The "coin-tap" test has the ability to indicate damage in a structural element due to a localized change of stiffness or damping. The change in vibration signature may be detected by ear or more precisely by measurement of the dynamic contact force. A method for discriminating between measurements made on sound and damaged structures is presented. An unsupervised neural network algorithm is used for recognizing the differences between contact force patterns. The method is used for non-destructive inspection of corrosion damage to steel chequer plate floors in industrial buildings. It is shown that the intelligent tap test is a useful and practical diagnostic tool for detecting localized damage in structures.
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1. INTRODUCTION

Steel chequer plate is often used in industrial buildings where it provides a convenient flooring system spanning between I-beams of the main structural steel framework. At chemical works many such buildings are used for the storage or production of corrosive chemicals which, in situations of elevated humidity, result in an aggressive environment. Under these circumstances the gap between the chequer plate and the beam to which it is fixed may trap moisture leading to the development of corrosion products, ultimately compromising the strength of the flooring [1]. Visual inspection is usually difficult due to limited access to the chequer plate from below, particularly when it requires the removal of ceiling coverings from the lower storey. Effective inspection often has to be carried out by unbolting and lifting out individual chequer plates from above. This is a tedious and expensive procedure. There exists a need to detect corrosion by testing from the upper surface of the chequer plate where access is easy.

The method proposed for inspection of steel chequer plate floors is a development of the "coin-tap" test of Cawley and Adams [2]. In this method the surface to be tested is tapped or struck. A damaged surface is usually identified by being less stiff than the sound material, resulting in a lower frequency note from the impact. Cawley and Adams measured this quantitatively using a hammer with a force transducer and recorded the interacting force impulse, which could be subsequently analyzed by examining its

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frequency spectrum. This technique enabled them to distinguish between localized areas of different stiffness.

In addition, damaged material may possess greater damping, hence attenuating the vibration. The method has been developed further by applying pattern recognition techniques to these more complex signals from the impact hammer [3]. In particular, neural network algorithms have been found to be very effective for detecting the differences between the signals obtained from sound and damaged structures [4].

2. CHEQUER PLATE FLOORING SYSTEM

The region of flooring tested, shown in Figure 1, was directly above one of a series of small I-sections that supported the third floor of a packing shed for the production and storage of ammonium nitrate fertilizer. The region that was chosen for testing is shown in Figure 2. The flooring comprised 8 mm thick chequer plates fixed at regular intervals along their long edges to the flanges of two small I-sections by five steel bolts with countersunk heads, as indicated in Figure 2(a). The short edges of the chequer plate were supported by two larger I-sections that were perpendicular to the small I-sections. Visual inspection of this beam from the lower floor showed that, at the mid-span region, corrosion products were packed at its interface with the chequer plate, whereas the regions towards its ends were relatively free from corrosion. These regions were categorized as "corroded" and "sound" respectively. There were also intermediate regions where the condition was ambiguous because corrosion products were not clearly visible from the lower floor although they might have been present. These regions were categorized as "suspect".

3. THE "COIN-TAP" TEST PROCEDURE

The "coin-tap" test is carried out by applying an impact using a hammer with a force transducer connected to a portable signal processor. Testing of the chequer plate floor is

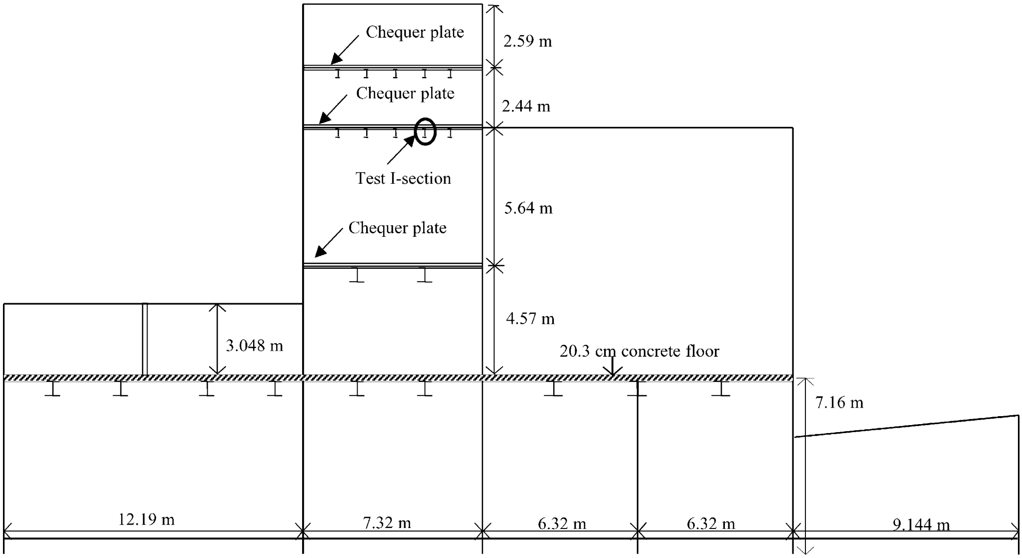

Figure 1. Section through fertilizer packing shed.

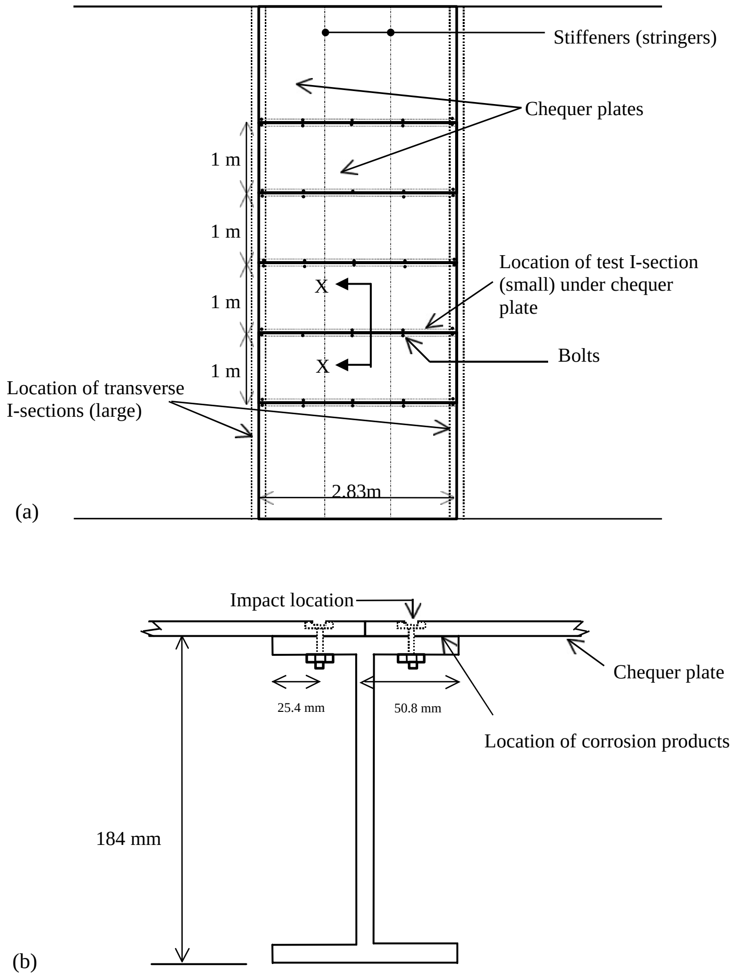

Figure 2. Detail of chequer plate flooring structural system. (a) Plan of third floor; (b) Section X-X.

shown in Figure 3. The convenience of the method may be seen clearly. The chequer plate floor is tested from above and the equipment is light and portable. The standard test procedure consists of recording both the force–time waveform and the frequency spectrum averaged over three impacts.

One measurement of the impact force was taken at each of 40 equally spaced positions along the longer edge of the chequer plate that was supported by the test I-section. Measurements were taken directly above the flange along the line of the fixing bolts. Therefore, five of the measurements corresponded to impacts on bolt heads as indicated in Figure 2(b). A heavy duty hammer fitted with an aluminium tip was used (see Figure 3). The time histories and frequency spectra were acquired with the spectrum analyzer using a rectangular window, a bandwidth of 10 kHz and a frequency interval of 6·25 Hz. The sample rate was 25 kHz (40 μs between samples). Each measurement was obtained by performing a process average on the time histories and frequency spectra acquired from three impacts at a particular position on the chequer plate. Figure 4 shows the force

Figure 3. Applying the tap test to chequer plate flooring.

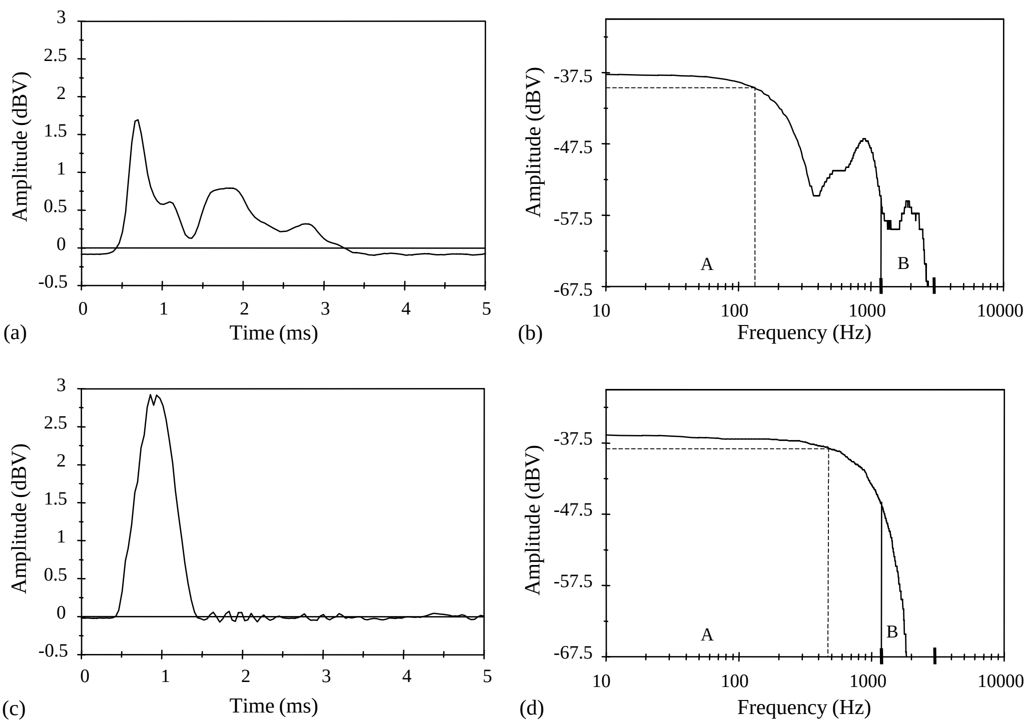

Figure 4. Force waveforms and frequency spectra for impact on chequer plate. (a) Time history of sound region; (b) Spectrum of sound region; (c) Time history of corroded region; (d) Spectrum of corroded region.

waveforms for typical impacts over two regions, the first known to be sound and the other corroded.

Figures 4(a) and 4(c) both show that the presence of corrosion products under the point of impact has the effect of damping the structural vibrations of the chequer plate. This is evident because the time history of the sound region exhibits high-frequency "ringing". Undamped structural vibrations feed back into the hammer's force transducer. In contrast, these vibrations are damped out rapidly by the corroded region resulting in a simple, clean force–time impulse as shown in Figure 4(c). The apparent impulse duration of the sound region is also greater than for the corroded region because of these vibrations. This effect is also indicated by comparing the frequency spectra shown in Figures 4(b) and 4(d). The spectrum of the sound region exhibits peaks corresponding to modes of vibration at 950 and 1900 Hz, whereas the spectrum of the corroded region shows no such peaks.

In the method of Cawley and Adams [2] two numerical quantities were evaluated from the frequency spectra. These were then used as discriminators between sound and damaged regions. The first quantity is the "cut-off" frequency. This is defined as the frequency at which the spectral amplitude is 2 dB less than the amplitude at zero frequency. This frequency is not influenced by variations in hammer velocity during impact since it depends on stiffness. In the spectra shown, the cut-off frequency of the sound region is approximately 138 Hz, whereas for the corroded region it is approximately 481 Hz, as indicated by the broken lines in Figures 4(b) and 4(d). This is due to the relative increase in structural vibration of the sound region compared with corroded region.

The other quantity used by Cawley and Adams [2] was also derived from the frequency spectrum as illustrated in Figures 4(b) and 4(d). It is based on the observation that a stiffer material will display more high-frequency content in the spectrum. The frequency spectrum was divided into two areas by an arbitrary threshold frequency (v_t) close to the maximum frequency (v_{max}) at the first minimum amplitude. In the case of the chequer plate floors, the threshold frequency was 1·2 kHz corresponding to 40% of the maximum frequency (3 kHz). The discriminator quantity was defined as the ratio of area, R_f, of the high-frequency area B to the total area enclosed below the maximum frequency:

$$R_f = B/(A + B). \tag{1}$$

These areas are shown in Figures 4(b) and 4(d).

The "cut-off" frequency and ratio of areas of frequency spectrum were used together to discriminate between sound and unsound regions, as shown graphically in Figure 5. It may be seen that measurements over the sound regions are clustered in the lower left of the plot whereas those over the corroded regions are clustered in the upper right. Measurements made over the suspect regions were grouped with those corresponding to corroded regions in the upper right of the distribution, suggesting that the suspect regions were actually corroded.

Measurements on the bolts were also grouped with measurements on corroded regions suggesting that the force waveforms were similar and that the bolts also suppressed vibrations of the chequer plate. These results confirm that the coin-tap test can discriminate measurements over corroded regions of the I-section from measurements over sound regions. It is evident from Figure 4 that the success of the discrimination in this case is due to the effect that corrosion has on damping of the vibrations under the impact. The corrosion damps out the higher frequencies resulting in a smooth impact force/time curve and a flat frequency spectrum. In contrast the sound steelwork transmits high-frequency vibration or "ringing" back into the force transducer, resulting in a distinctly

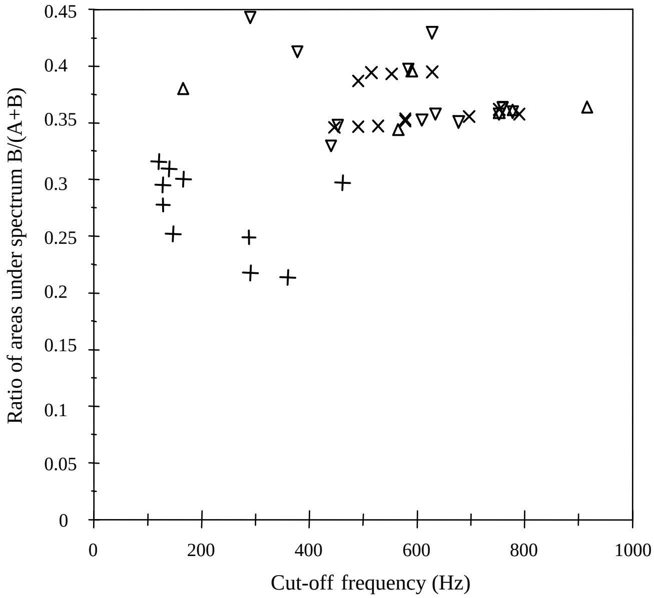

Figure 5. Cut-off frequency versus ratio of areas under spectrum. + Sound region; × Corroded region; ▽ Suspect region; △ Bolts.

different force/time curve and spectrum. The next section describes a method of pattern recognition employed to perform this task automatically.

4. NEURAL NETWORK PATTERN RECOGNITION

An important objective of this research was to process the impact data using a pattern recognition algorithm so that discrimination between sound and unsound structures can be achieved automatically. It is envisaged that an inspector would "train" the algorithm by impacting sound structures, so that impacts on structures of unknown condition could be classified as sound or novel in behaviour.

Computational methods have been applied to the recognition of printed characters and to differences between graphical displays such as waveforms. The latter application is relevant to this study. The general procedure is to extract a suitably representative feature vector from the waveform and present it to an algorithm that will classify it according to different classes of feature vectors that have previously been presented. The classification should be on the basis of probability so that exact matches of waveforms are not required, only the general shape to a defined level of accuracy.

Neural networks have a superficial resemblance to the operation of the human brain, though in effect they compute the probability of a class of membership for a feature vector [5]. "Supervised" classification is achieved by assigning each input training vector to a specified class so that the coefficients in the neural network produce an output corresponding to the class of the input. A test input vector is then presented to see what output is produced so that it can be classified accordingly. "Unsupervised" learning is achieved by establishing the existence of classes amongst a set of input feature vectors on the basis of probability distributions. The latter method is useful when there is no clear pre-determined set of classes.

In this investigation an unsupervised pattern recognition algorithm was used since the only known pre-determined class would be "sound" condition. The algorithm used was the probabilistic resource allocating network (PRAN) published by Roberts and Tarassenko [6]. The operation of the algorithm is illustrated in Figure 6. A feature vector consisting of the amplitudes of a waveform, denoted by ξ_1, ξ_2, ξ_3, etc., are presented at the inputs to the network as shown in Figure 6(a). The output unit or kernel, denoted by V_1, consists of a Gaussian probability density function $\phi(\mathbf{x}_i; \mathbf{m}_i, \mathbf{F}_i)$ where $\mathbf{x}_i$ is a d-dimensional input training vector, $\mathbf{m}_i$ is the current location of the kernel in d-dimensional space, and $\mathbf{F}_i$ is its covariance matrix. The Gaussian function $\phi(\mathbf{h})$ is shown in Figure 6(b) where the vector $\mathbf{h}$ is the difference between the feature vector and the vector $\mathbf{m}$, representing the mean of the kernel. Hence $\mathbf{h}$ is given by

$$\mathbf{h} = \boldsymbol{\xi} - \mathbf{m}. \tag{2}$$

The standard deviation of the kernel is represented by $\boldsymbol{\sigma}$.

Training is achieved by updating the means $\mathbf{m}_i$ and covariances $\mathbf{F}_i$ at each presentation of a training vector $\mathbf{x}$. If the response $\phi(\mathbf{x})$ of a new input vector is less than a defined threshold, then a new kernel is grown denoted by V_2 as shown in Figure 6(c). Training proceeds until no training data meets the growth criterion during presentation of the entire set of input vectors. Full details of the algorithm are given by Roberts and Tarassenko [6].

There are two empirical quantities that have to be established during the training of a set of input feature vectors. The first is an adaptation parameter that is chosen from experience to operate the algorithm efficiently. The second is the growth threshold mentioned above. This represents a distance from the location of the existing kernel and depends on the location (mean) and spread (standard deviation) of the kernel. The threshold distance is best chosen empirically by observing the results after a preliminary run of the training data. If there are too many output kernels then the threshold can be

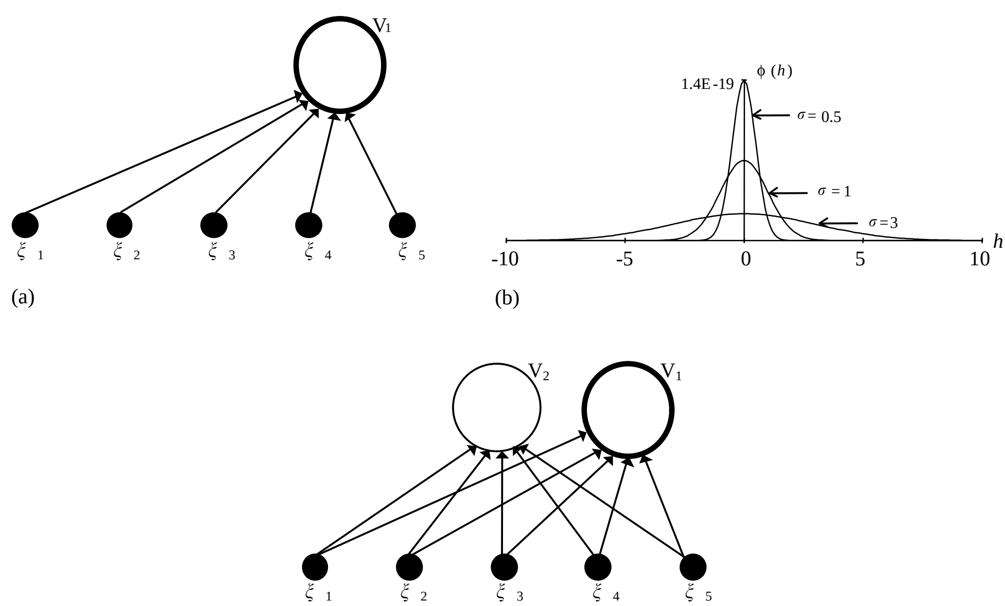

Figure 6. The probabilistic resource allocating network. (a) Initial architecture; (b) The Gaussian Function; (c) Architecture after growth of one additional unit.

increased until the training data yields about two or three kernels. The results may be presented visually by means of a principal component analysis. The principal components of a vector are those that exhibit the highest variance from one vector to another. The two highest principal components of the vectors may be plotted on cartesian axes together with the mean, **m**, and variance, **F**, for each kernel. This is illustrated in Figure 7. The two highest principal components are denoted by ξ_1 and ξ_2. The variances of the four kernels are shown by error bars that intersect at their means. There is one large kernel with two lesser kernels and a fourth very small kernel. The three larger kernels may be associated with sound material, whereas the fourth kernel is somewhat removed from the others and is sparsely populated, indicating novel behaviour that may be associated with damage.

5. RESULTS AND DISCUSSION

The frequency spectra produced by impacts on the chequer plate flooring were sampled to form feature vectors that represented the normalized spectrum over a 3 kHz frequency range (see Figure 8). The feature vectors each had 48 components obtained by sampling at 50 Hz intervals between 0 and 250 Hz (eight components) and at 68·75 Hz intervals between 250 and 3 kHz (40 components). This distribution was chosen purely for convenience. The unsupervised probabilistic resource allocating network (PRAN) was trained by cyclically presenting it with feature vectors obtained from the 40 measurements at positions along the I-section. A preliminary analysis of the data indicated that the probability distribution could be represented by two kernels. Therefore, the PRAN was trained to grow two units by repeatedly training and adjusting the parameters appropriately.

A principal component analysis, as explained above, was then performed on the feature vectors. It was found that the first two principal components of the feature vectors were the 16th and 17th, corresponding to 950 and 1018·75 Hz. The locations of the principal components on the normalized spectra are indicated by the broken lines in Figure 8 and these show that their magnitudes in the sound region are less than those in the corroded region. In Figure 9 the measurements on the chequer plate are plotted on orthogonal axes corresponding to the two principal components. The measurements are indicated by four symbols, one for each category assigned to the condition of the interface between the I-section and the chequer plate. Some of the vectors with the same symbol overlap, leading

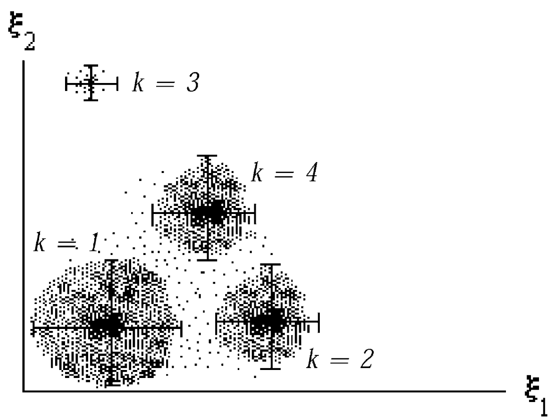

Figure 7. Principal component visualization after training.

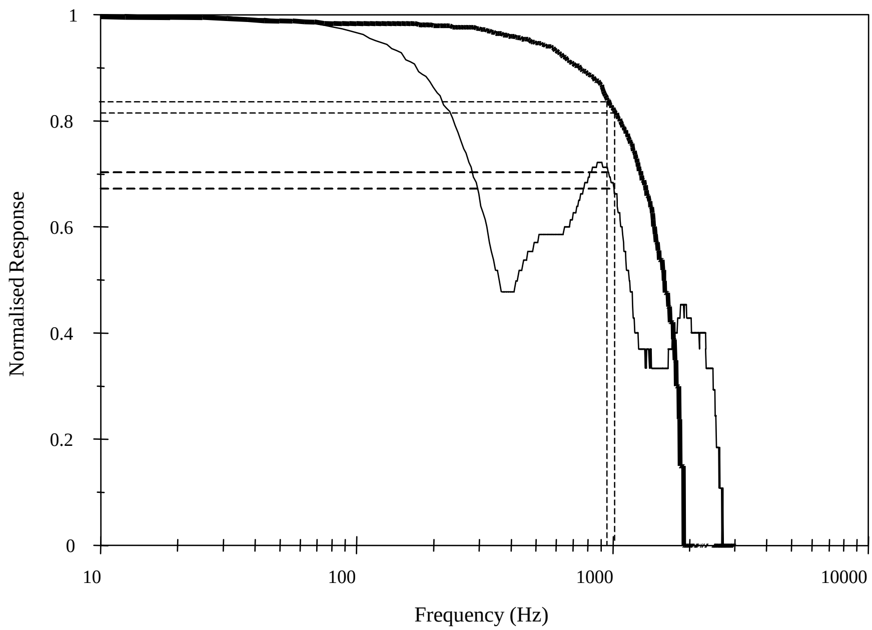

Figure 8. Normalized spectra of impact force on chequer plate (log x-axis). ——, Sound; ▬▬, Corroded; – – – –, Principal componments.

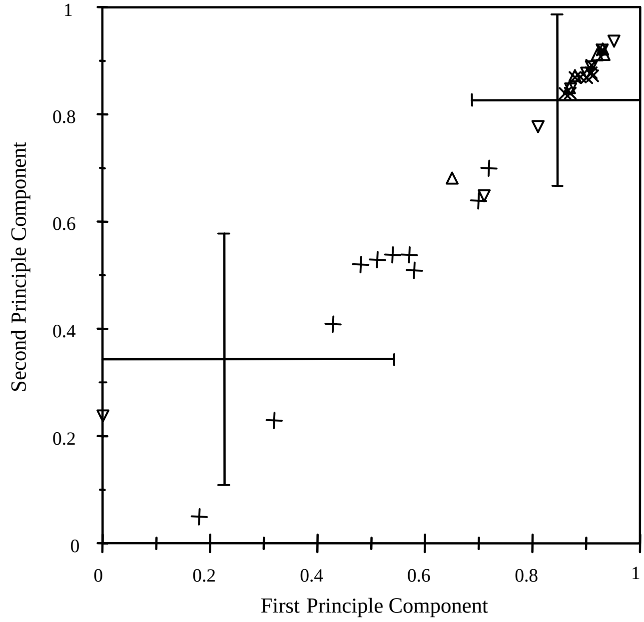

Figure 9. Principal component analysis of impacts on chequer plate. + Sound; × Corroded; ▽ Suspect; △ Bolts.

to an apparent discrepancy in the number of measurements. The kernels are shown by intersecting error bars, the lengths of which correspond to the standard deviations, while the points of intersection are the means.

The measurements over the corroded regions are in a densely populated part of the figure, whereas measurements over the sound regions are in a sparsely populated area. It must be remembered that the plot in Figure 9 is a projection of the feature vectors onto a two-dimensional plane. The PRAN used all 48 components of the feature vectors to classify. Measurements on the bolts and measurements on suspect regions were clustered with measurements on corroded regions. This confirms the observation made earlier that the suspect regions were actually corroded, and that the response of the bolts was similar to that of the corroded regions because both exhibited damping of the vibrations of the chequer plate. In practice, the grouping of the bolt data with the corroded region should not matter since the operator would be aware when bolts are impacted.

These results demonstrate the usefulness of the unsupervised probabilistic resource allocating network (PRAN) in this application. The condition of the interface between the chequer plate and the supporting I-section at the exact position of impact is not known without the tedious task of lifting the chequer plate for examination. However, the algorithm formed two clearly defined clusters of data from measurements on the chequer plate corresponding to corroded regions and sound regions. Provided that the network had already been trained on a chequer plate known to be sound, any subsequent test would indicate if it were associated with the "sound" cluster or otherwise.

6. SUMMARY AND CONCLUSIONS

The intelligent "coin-tap" test was applied to industrial chequer plate flooring and was shown to be effective for distinguishing locations of significant corrosion. The corrosion products between the chequer plate and the supporting I-section were found to damp structural vibrations of the chequer plate when impacted and therefore the resulting force waveforms were distinctively different from those obtained by impact over sound regions.

An unsupervised neural network pattern recognition procedure was appropriate for inspection of chequer plate flooring because only one pre-determined classification was available for training, namely "structurally sound". During subsequent testing, unsound regions were then apparent as distinctly separate data clusters and therefore could be classified as novel.

The equipment required is light and portable and is capable of being developed into a convenient diagnostic tool for on-site inspection.

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