Clustering-based Automatic Diagnosis of Concrete Condition Using Hammering

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1. Introduction

Concrete structures are the most common type of structure found in modern societies. These structures can be greatly affected by aging and environmental conditions. In some cases, these factors may lead to structural failure [1]. In order to guarantee their safe use, careful maintenance is needed. Diagnosis for defects is then critical since it is a decision-making step.

One wide-spread method to test a concrete structure for defects is called hammering test (Fig. 1). This method, consisting of an operator hitting the surface of the structure with a hammer and assessing the presence of defects from the perceived sound, has the advantages of being non-destructive and not needing heavy equipment. However, it requires a skilled operator to be able to correctly analyze the sound and given the huge population of structures in need of examination currently in service, testing them all with this traditional method reveals to be problematic.

Various attempts to adapt the hammering test in an automatic form have been made in order to obtain a faster, reliable and objective method to find defects in concrete structures. [2] and [3] were focused in finding sound features enabling differentiation between defective and non-defective spots as well as on the exploration of new methods to replace or aid the human operator holding the hammer in order to get more regular and reliable sound samples. [4], [5], [6] and [7] were more focused on the data analysis part of the problem and use supervised learning to correctly distinguish sounds from non-defective areas and sounds from defective areas. These approaches have given promising results, however their main drawback is the necessity to train the algorithm first using a training set. Depending on various factors, concrete can greatly differ from one structure to another thus choosing the adequate training set can be difficult.

In this paper, we present an approach to automated diagnosis of concrete condition using hammering based on clustering by a k-means algorithm. This method relies on data collected on the actual tested structure only and does not need the use of any new equipment but a traditional hammer.

2. Irregularity quantification

2·1 Concept

The main hypothesis this method is based on is that most of the tested structure is non-defective i.e.

Fig. 1 Hammering test conducted by a professional

the most commonly found sound on the structure, the regular sound, can be identified as being of a non-defective area. Therefore, if a large group of similar sounds can be distinguished in the dataset, it can be inferred that it is the regular sound of the structure and a model representing the regular, non-defective sound of that structure can be made. Simple clustering algorithms, such as k-means, can effectively accomplish this task. This regular model can then be used as a reference to conduct a diagnosis of the whole dataset.

After witnessing professional workers on the field and interviewing them, it can be deduced that this is subconsciously done by human operators when conducting a hammering test: rather than directly recognizing a sound for being either defective or not, they hit multiple locations on the structure and access the spot that returns a sound different than the others as being a defective spot.

2·2 Feature vector and dissimilarity measure

Fourier spectrum is used as feature vector for a hammering sound sample. Given a sound sample defined by $(x_0, ..., x_{N-1})$ recorded on the structure, its Fourier spectrum $(a_0, ..., a_{N-1})$ as defined in equation (1) is obtained using Fast Fourier Transform (FFT).

$$a_j = \sum_{l=0}^{N-1} x_l e^{-\frac{2\pi i}{N} jl} \qquad j = 0, ..., N-1 \tag{1}$$

In order to compare sounds, a meaningful distance measure between sound samples in the Fourier spectrum space has to be defined.

Given two Fourier spectrum a and b, respectively defined by $(a_0, ..., a_{N-1})$ and $(b_0, ..., b_{N-1})$, the sample

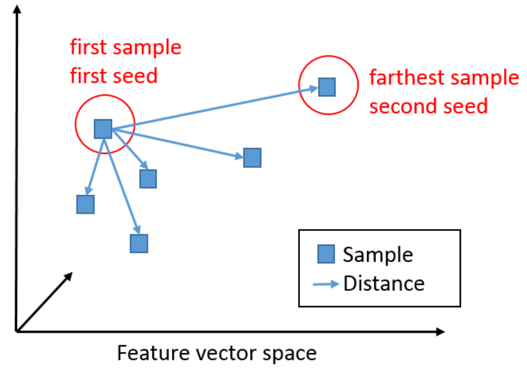

Fig. 2 After selecting the first sample as seed, its farthest sample is defined as the second seed

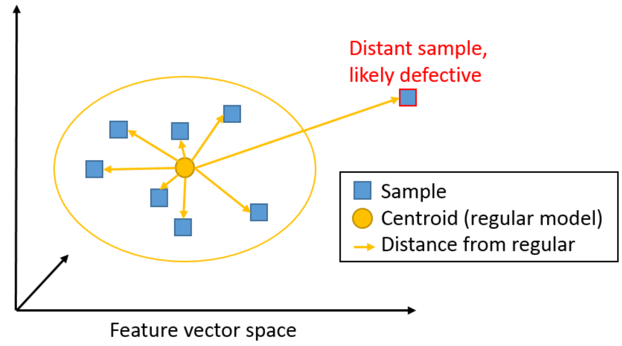

Fig. 3 By calculating distances from the biggest cluster's centroid, irregular sample(s) can be found

Pearson correlation coefficient is defined as in equation (2).

$$r_{ab} = \frac{\sum_{l=0}^{N-1}[(a_l - \bar{a})(b_l - \bar{b})]}{\sqrt{\sum_{l=0}^{N-1}(a_l - \bar{a})^2}\sqrt{\sum_{l=0}^{N-1}(b_l - \bar{b})^2}} \quad (2)$$

The sample Pearson correlation coefficient has the advantage of providing a zero mean and unit standard deviation normalizations. Features of the Fourier spectrum of each sound sample used for comparison are only related to the general shape and amplitude variations are not taken into account. Therefore, it can be considered robust towards changes of the force applied by the human operator of the hammer that induces sounds of different amplitude being recorded.

The sample Pearson correlation coefficient ranges in [-1,1]. Negative values signifies a negative correlation, and positive values corresponds to correlation. Values close to zero implies there is no correlation between the two samples. We can define a distance measure based on this coefficient, a correlation distance, as in equation (3).

$$d(a,b) = \frac{1 - r_{ab}}{2} \quad (3)$$

The defined distance is ranging in [0,1], returning small values the more the compared sounds are alike and zero if the sounds are identical. Cases of negative correlation are located in the [0.5,1] range since negative correlation is in our case not a similarity.

2·3 Clustering based model generation

Regarding the seeds for the k-means algorithm, they need to be as distant as possible, in terms of the distance as previously defined in equation (3). A simple implementation is to choose the first sample as a first seed and then parse the rest of the sound dataset to find the most distant sample, which would be set as the second seed (Fig. 2).

K-means clustering algorithm is applied using the correlation distance defined in equation (3) to classify the sound dataset in two clusters. Then, the number of samples in each cluster is counted and the biggest one is identified as the regular cluster i.e. the cluster containing non-defective samples. The centroid of this cluster is used as a model for the regular, non-defective sound that should be found on the structure.

2·4 Diagnosis

Each sound sample of the dataset is finally compared to the model using once again the correlation-based distance defined in equation (3) i.e. the generated regular model is used as reference to scale and evaluate the samples. Since the model represents the most regular sound shape in the dataset, irregularities i.e. distant sound samples can be recognized as characteristic of defects on the structure (Fig. 3).

3. Experiments

3·1 Setup

The used setup is illustrated in Fig. 4 and experiments were conducted on three concrete test blocks. The first one without any defects (Fig. 5a) used as a reference, the second one with an artificial crack at an angle of 15°(Fig. 5b), to simulate delamination that occurs on the field, and the third one with an artificial crack at an angle of 30°(Fig. 5c), to simulate a deeper delamination. For each block in Fig. 5, defective spots are marked in red.

Each test block was hit at 196 locations once following a 14 by 14 square grid (marked with white dots on the surface of the block) that covers the whole block. The used hammer was a KTC UDHT-2 (head diameter 16 mm, length 380 mm, weight 160 g), commonly used in hammering test by professionals and sound was recorded at 44.1 kHz using a Behringer

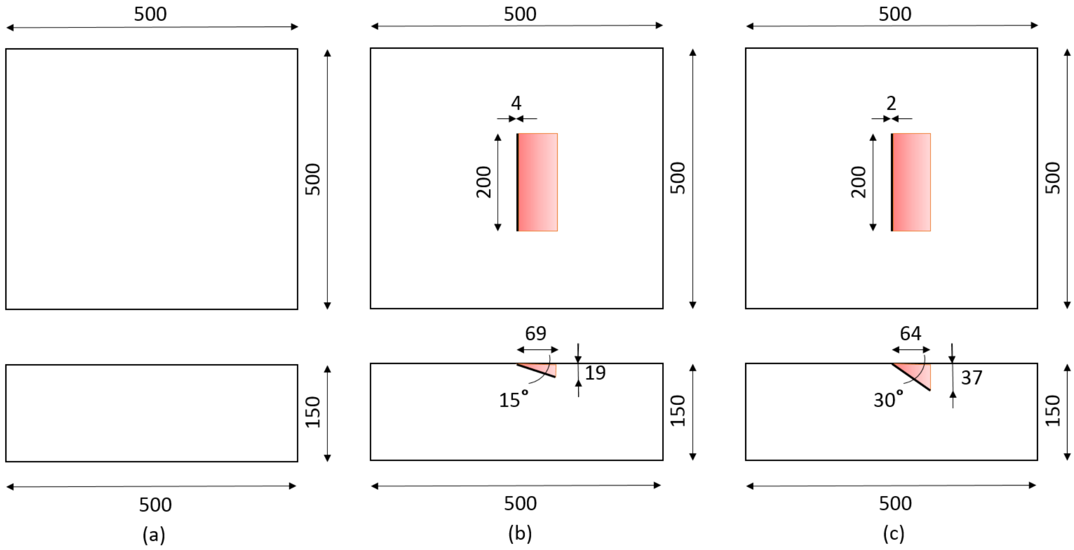

Fig. 5 Schematic of (a) the non-defective test block, (b) the 15°crack test block and (c) the 30°crack test block (lengths given in mm)

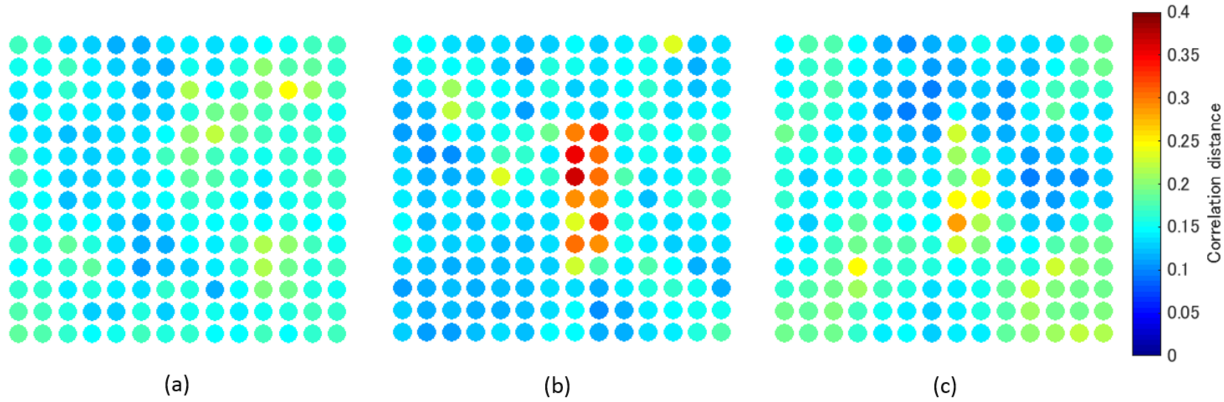

Fig. 6 Visualized distances on (a) the non-defective test block, (b) the 15°crack test block and (c) the 30°crack test block

ECM8000 microphone coupled with a Roland UA-25EX sound board and a laptop for data analysis. A simple trigger was implemented to conduct clipping to get each hammering sound as a single sample.

3·2 Results

FFT was applied to each sound sample for 1024 points. Due to the symmetry of the Fourier spectrum, the feature vector of each sound sample was then reduced to simply 512 points.

In order to ignore sound similarities induced by environmental noise, a simple spectrum subtraction was used [8].

To focus on positive correlation, results are displayed in Fig. 6 using a color scale ranging in [0,0.4] for a better contrast. As it can be seen, the method correctly identifies defects (tested spots right over the crack) as having a sound that is distant from the generated regular model.

3·3 Performance

In order to quantify the effectiveness of our method, Receiver Operating Characteristic (ROC) curve was computed on the previously presented defective test block.

The schematic in Fig. 5 was used as ground truth: samples collected directly above the crack were considered defectives and all the others non-defectives. Then, different values of threshold were used to determine whether a sample was defective or not based on the previously calculated distance from the regular model.

Cases where a non-defective sample was considered defective are called false positives and cases where a defective sample was correctly considered defective are called true positives. Plotting the true positive rate against the false positive rate at various threshold settings enables to create the ROC curve

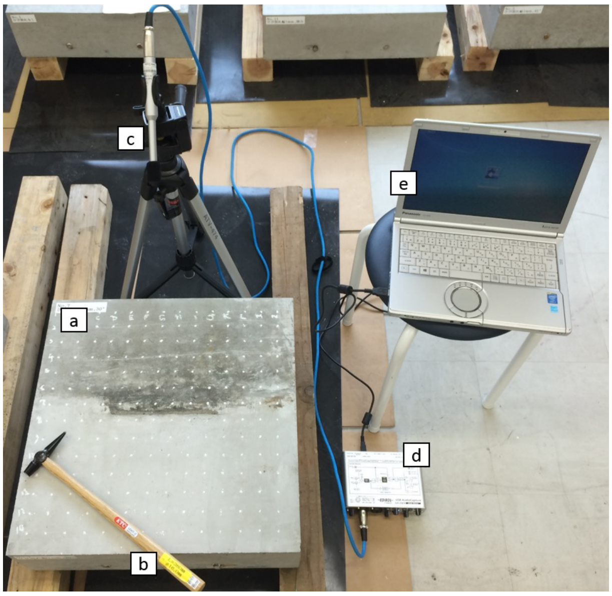

Fig. 4 Experimental setup: (a) a concrete test block, (b) a percussion hammer, (c) a microphone, (d) a sound board and (e) a laptop

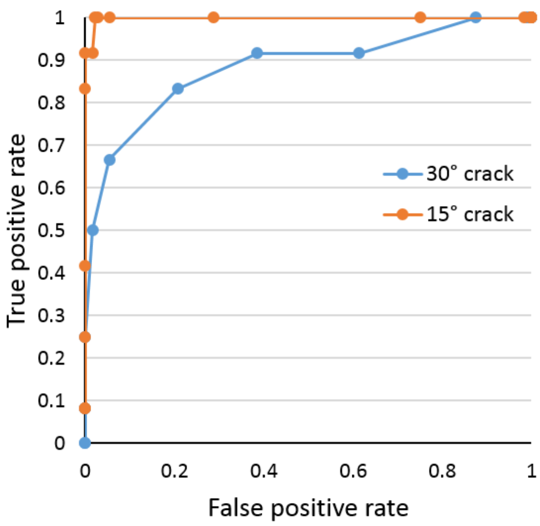

Fig. 7 ROC curve for the 15°and 30°cracks

shown in Fig. 7.

Bigger is the area under the ROC curve, better is the method. For the 15°and the 30°crack block, it was calculated at respectively 0.998 and 0.884. Both values being very close to 1, it confirmed the high efficiency of our proposed method during the experiments.

4. Conclusion

As for now, the method described in this paper was able to correctly detect defects up to a 30 °crack. In future works, we would like to improve and further test this method in order to detect other various irregular states. Tests on real, natural defects on concrete structure are also to be conducted. For an easier use on the field, implementing this method to be real-time, for example by using online k-means, is under consideration.

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