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# DATA MINING FOR ACOUSTIC EMISSION MONITORING OF A NUCLEAR CONTAINMENT WALL DURING POST-TENSIONING

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## ABSTRACT

This study introduces data mining for acoustic emission (AE) monitoring of containment structures. As being post-tensioned, hidden delamination cracks may develop in these structures and remain undetected. Since concrete cracking emits acoustic noises, advanced data mining techniques are here introduced to recognize common patterns in such AEs. Specifically, non-linear dimensionality reduction, k-mean clustering, and hidden Markov modelling are used. Validation performed on a large-scale, curved concrete wall shows, interpreting the physical meaning of AE patterns allows early detection of delamination.

## INTRODCUTION

Containment structures are cylindrical, often post-tensioned, concrete structures that serve as the final barrier against contaminating radioactive materials. In the curved walls of nuclear containment structures, hidden delamination defects may develop. This is due to the radial through-thickness tensile stresses introduced by post-tensioning. Such defects, if remain undetected, may lead to premature brittle failure of the containment structure. For example, in 2009, the containment structure of the Crystal River 3 nuclear power plant was identified as delamination, which eventually led to its permanent shutdown (International Performance Improvement 2010).

Several non-destructive testing (NDT) methods can be used to assess the condition of concrete structures (Davoudi et al. 2018a; b; Dorafshan et al. 2018; Dorafshan and Maguire 2018; Ebrahimkhanlou et al. 2015, 2016, 2019a; Ebrahimkhanlou and Salamone 2017b; Sun et al. 2018). AE is a promising method among them that relies on a network of sensors and an acquisition system to collect any internal burst of energy in the form of acoustic waves. Examples of such energy bursts include concrete cracking, which is an indicator of structural degradation. To quantify the structural degradation based on AE, many researchers have investigated the patterns of AE waves (Grosse and Ohtsu 2008; Miller and Hill 2005). For example, k-means clustering (Calabrese et al. 2012; Godin et al. 2004; Gutkin et al. 2011; McCrory et al. 2015; de Oliveira and Marques 2008), b-value analysis (Aggelis et al. 2010; Colombo et al. 2003; Ebrahimkhanlou et al. 2019e; Elbatanouny et al. 2014; Farhidzadeh et al. 2013; Schumacher et al. 2011), reverberation analysis (Ebrahimkhanlou et al. 2019c; d; Ebrahimkhanlou and Salamone 2017a; c; d), and hidden Markov modelling (HMM) (Wenfan Zhou et al. 2009) have been introduces to interpret AEs. However, to the best of the authors' knowledge very little research is available on AE monitoring of containment structures, and thus data mining on their AE.

The objective of this study is to use AE to monitor a large-scale containment structure as it is being post-tensioned (Choi et al. 2017). In particular, the goal is to interpret AE in terms of the failure mechanism and use such interpretations to detect the moment at which delamination cracking initiates (Ebrahimkhanlou et al. 2018, 2019b). The challenge is to mine AE data and find meaningful trends in the data that explain the physics of delamination. In particular, the first challenge in this direction is to efficiently cluster AE waveforms that stem form tensile or shear cracks. Then the next challenge is to relate each cluster to the state of stress in the structure and the probabilistically explain the failure mechanism.

## DATA MINING OF ACOUSTIC EMISSIONS

This study uses advanced data mining techniques to recognize common patterns in the AE signals. The first step is to cluster AE signals using k-means clustering. In particular, clustering is applied on nine AE features: amplitude, average signal level, initial frequency, average frequency, frequency centroid, peak frequency, and rise time, duration, absolute energy. To assign AE features $X = \{x_1, ..., x_9\}$ into $K$ clusters, $C_1, ..., C_K$, the algorithm randomly divides the data into $K$ groups and iteratively adjusts the memberships so that each cluster's mean, $\mu_1, ..., \mu_K$, minimize the following (Bishop 2006):

$$E(\mu_1, ..., \mu_K) = \sum_{i=1}^{K} \sum_{x_j \in C_i} \left\| x_j - \mu_i \right\|^2 \tag{1}$$

In this equation, $\| \cdot \|^2$ is the Euclidian distance. To determine the optimal number of clusters, $K_{opt}$, the average Silhouette index is used (Bishop 2006). To visualize these nine features and verify the clustering quality, a nonlinear dimensionality reduction approach, specifically, Isomap (Tenenbaum et al. 2000) is used. Isomap allows visualizing this high-dimensional data in a three-dimensional space.

Since AE signals are sequentially recorded one after another and each signal belongs to a cluster, the entire AE data is a sequence of clusters. To model this sequence, this study uses an HMM. This model probabilistically explains the sequence of the clusters based on the damage state of the structure. The damage state is initially intact, but at some point during the post-tensioning makes a permanent transition to the delaminated state. Therefore, the HMM allows us to detect the onset of delamination by identifying the moment of the transition. The HMM describes the sequence of observed variables $O$ (i.e. AE clusters) in terms of underlying hidden (latent) valuables $H$ (i.e. the delamination state: intact or delaminated) (Bishop 2006). In other words, each observed variable $o_i$ has a conditional probabilistic dependence on a hidden variable $h_i$. This conditional dependency is described as $P(o_i | h_i)$. The hidden variables also sequentially depend on their previous states. This probabilistic dependency can be explained using a binomial distribution: $P(h_i | h_{i-1})$. Figure 1 visualizes the probabilistic dependency of hidden and observed variables. For a sequence of $N$ acoustic waves, such dependencies can also be expressed mathematically:

$$P(H, O) = P(h_1) \prod_{i=2}^{N} P(h_i | h_{i-1}) \prod_{j=1}^{N} P(o_j | h_j) \tag{2}$$

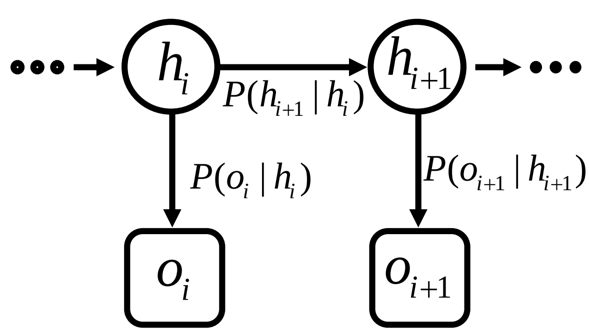


Figure 1. Hidden Markov model

## EXPERIMENT

For validation, a curved concrete wall was monitored during post-tensioning. The wall was designed to approximately represent 20% of the size of a typical containment structure (Choi et al. 2017). Specifically, it was 14′ (4.27 m) in diameter, 12″ (305 mm) in thickness, and 6′ (1.83 m) in height. The wall had no radial reinforcement and contained four uniformly spaced, 4″ (101 mm)-diameter prestressing ducts embedded in concrete with target design strength of 3500 psi (24.1 MPa). To apply and measure post-tensioning forces, four 800-kip (3560 kN) hydraulic rams and eight 1000-kip (4450 kN) load cells were utilized. The post-tensioning forces were monotonically increased until the wall failed due to delamination. Figure 2 shows the experimental setup. To record AEs, eight AE sensors (Physical Acoustic Corporation, R6α) were mounted on the outer surface of the wall. To have an alternative way to validate the onset of delamination, two linear strain conversion transducers, hereafter referred to as delamination gauges, were embedded through the thickness of the concrete (see Figure 2).

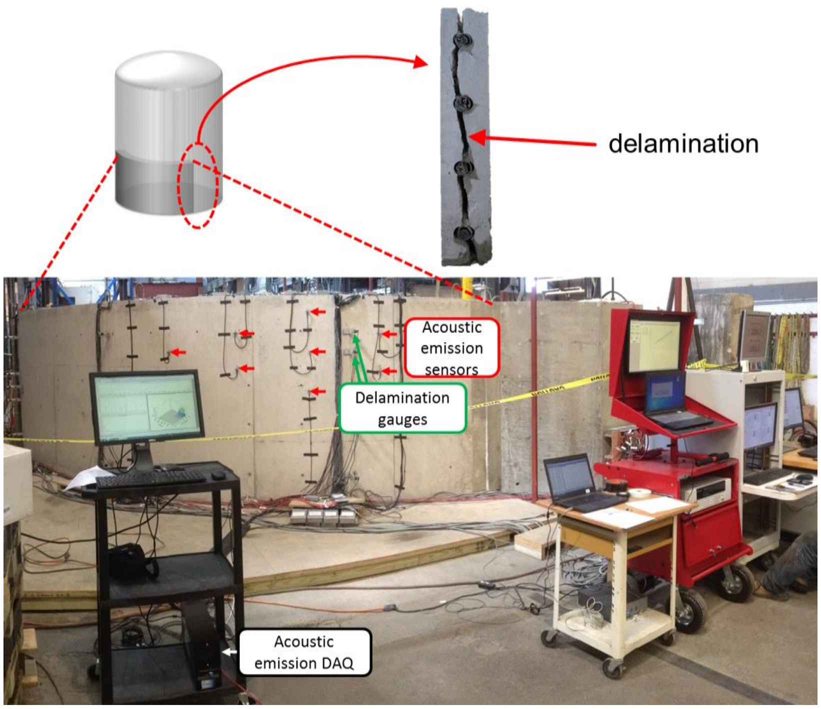


Figure 2. Experimental setup

## RESULTS

Figure 3 visualizes the location of AEs obtained using the AEwin software (MISTRAS, NJ, USA). Only the portion of the wall covered by AE sensors is shown in the figure. The results show a concentration of AEs around the area that eventually delaminated. Specifically, below the top duct, at 12° to 20° angles measured on the curvature of the wall.

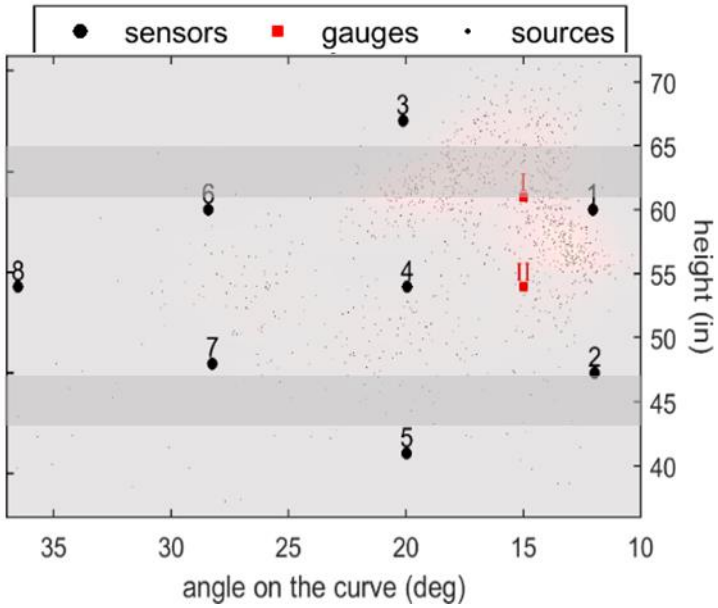


Figure 3. Localization of AE sources

Figure 4 shows that the optimal number of clusters was three. These clusters are respectively due to shear stresses causing micro cracks, tensile stresses causing micro cracks, and macro cracking during delamination. It is important to note that the uniaxial compression applied in this test impose shear stresses in the in-plane direction. On the other hand, radial stresses are tensile. The distinctive features of the third cluster include its high amplitude and long duration.

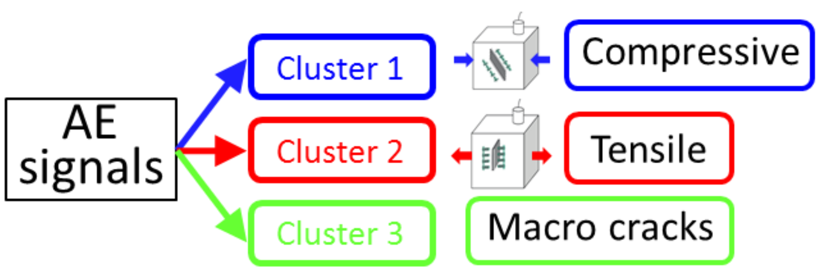


Figure 4. Optimal number of cluster and their physical interpretation

Figure 5 visualizes the three clusters in a three-dimensional space. In order to reduce the nine-dimensional feature space of the clusters and allow their visualization, a nonlinear dimensionality reduction (ISOmap) was used. The figure shows proper separation between the clusters. To ensure finding the optimal separation between the three clusters, clustering was repeated 2500 times with different initial guesses.

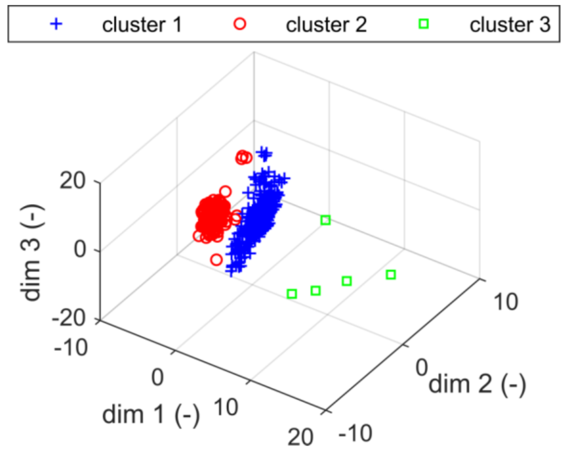


Figure 5. ISOmap visualization of clusters in three-dimensional space

Figure 6 shows the trained HMM for this study. As the figure shows, the transitional probability between the two hidden states is very low. This is consistent with the reality in which the wall remains un-delaminated for a large portion of the experiment, and then it makes the transition to the delaminated state and remains delaminated until failure. The figure also shows that the emission probability of cluster 1 and 2 respectively decrease and increase after delamination. Cluster 3 that generally has a low emission probability, becomes more common after delamination.

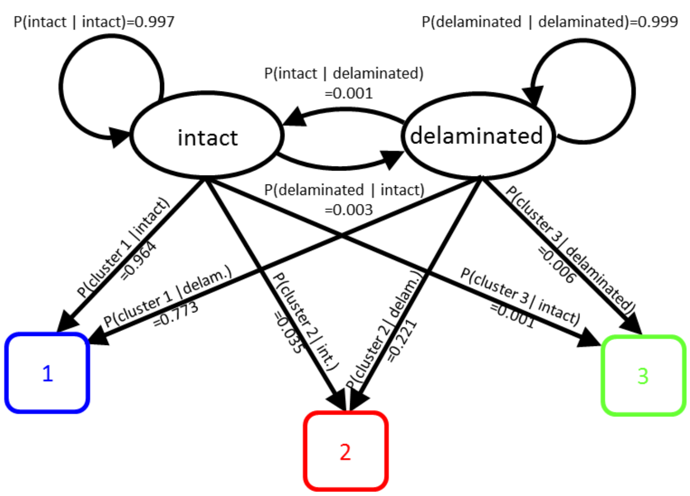


Figure 6. The trained hidden Markov model

Figure 7 compares the estimated hidden delamination state (i.e. intact or delaminated) with the results obtained from the delamination gauges. As the figure shows, the estimated delamination state made a permanent transition from the intact state to the delaminated state. The load at which this transition occurred approximately coincides with at the first indication of delamination recorded by the first delamination gauge. Therefore, the HMM model correctly estimated the condition of the wall.

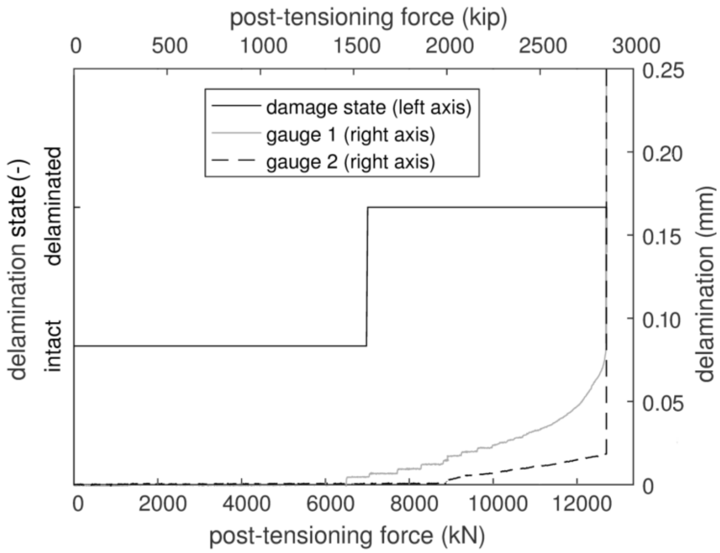


Figure 7. Delamination detection

## CONCLUSIONS

This paper presented AE monitoring of a large-scale experimental model of a nuclear containment structure subject to monotonically increasing prestressing loads. In particular, AE data was interpreted in terms of hidden delamination defect that may develop during the construction phase of this type of structures. The results show that the proposed approach can effectively detect the onset of delamination. These results prove that HMM combined with k-mean clustering of AE can provide an in-time alarm to take remedial and preventive actions against delamination defects in nuclear containment structures. In addition, this approach could also be used to monitor the post-tensioning and re-tensioning of other containment structures, such as silos, bins, and storage tanks. However, future research should focus on performing more experiments and consider in-field verification.

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