

Data aggregation for improved honeycomb detection in concrete using machine Learning – based algorithms

Christoph VÖLKER¹, Parisa SHOKOUHI²

¹ Bundesanstalt für Materialforschung und –prüfung (BAM),
Unter den Eichen 87, 12205 Berlin, Germany

Phone: +49 30 8104-1440 (secretariat of Division 8.2), e-mail: christoph.voelker@bam.de

² Department of Civil and Environmental Engineering, The Pennsylvania State University
215Sackett Bldg., University Park, PA 16802, e-mail: parisa@enr.psu.edu

Abstract

We present the results of several machine learning (ML)- inspired data fusion algorithms applied to multi-sensory nondestructive testing (NDT) data. Our dataset consists of Impact-Echo (IE), Ultrasonic Pulse Echo (US) and Ground Penetrating Radar (GPR) data collected on large-scale concrete specimens with built-in simulated honeycombing defects. The main objective is to improve the detectability of honeycombs by fusing the information from the three different sensors. We describe normalization, feature detection and optimal feature selection. We have used unsupervised and supervised ML, i.e., classification and clustering, for data fusion. We demonstrate the advantage of data fusion in reducing the false positives up to 10% compared to the best single sensor, thus, improving the detectability of the defects. The methods were evaluated on a concrete specimen. The effectiveness of the proposed approach was demonstrated on a separate full-scale concrete specimen. The results indicate the transportability of the conclusions from one specimen to the other.

Keywords: data fusion, concrete evaluation, honeycombing, machine learning, clustering

1 Introduction

In the recent years nondestructive testing methods in civil engineering developed greatly and became commercially available for a broad range of users. Applications in the field of condition assessment and structural analysis are promising as they enable precise repair measures and thus enhance ecological and economic efficiency drastically.

It is often necessary to deploy multiple NDT methods in order to achieve a comprehensive and reliable assessment [1]. Automated scanner systems facilitate the collection of high quality multisensory data [2]. Parallel data acquisition with robotics enables the assessment of impressively large test areas [3,4,5]. Data analysis is typically conducted independently for each test method by trained NDT personal. The assessment result is eventually achieved by the manual comparison of the individual testing results. Thus, the next logical step is to implement effective data fusion algorithms for automated data analysis. Improved information quality and a higher degree of reliability are the expected outcome [6,7].

In the presented case study we launched a three-sensor investigation on a large-scale concrete specimen with built-in simulated honeycombing defects. Honeycombs are porous volumes in concrete consisting mostly of coarse grain aggregates and cement paste. This defect is created either from granular convection or sieving of the concrete (at highly reinforced construction parts) while pouring it [8]. In the defective areas the concretes density is reduced. This results in a decrease load bearing capacity as well as a lower resistance to water penetration. Cracks and rebar corrosion may follow.

Since it is impossible to intentionally create well controlled honeycombing while pouring the concrete, they were pre-manufactured and located in the specimen before concreting. They were created by just filling coarse grain aggregates and cement paste in cylindrical formworks (diameter and height was 15 cm) [9]. By knowing the exact dimensions and locations of the honeycombs systematic investigations are enabled.

2 Experiments and Specimen

We collected ultrasonic pulse-echo (US) [10], impact-echo (IE) [11] and ground penetrating radar (GPR) [12] test data with an automated scanner system developed at BAM. The measurements were conducted on a 30 cm thick large-scale concrete slab. Its concrete cover is about 3cm and the spacing is of the 10 mm diameter rebar is 10 cm. Simulated honeycombing defects are built in three different orientations according to figure 1. Their concrete cover from the top is about 11cm.

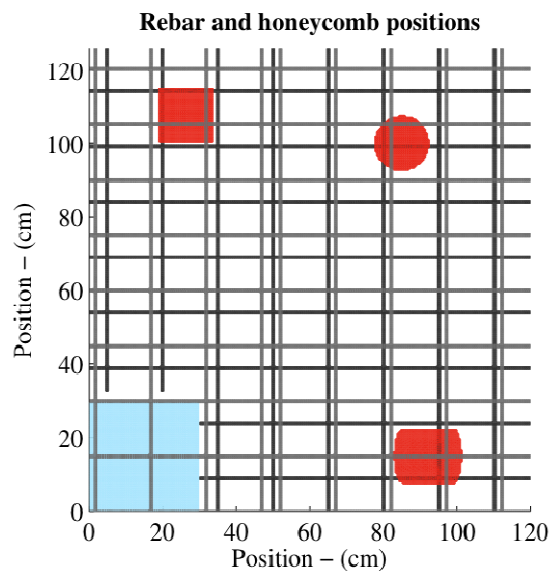


Figure 1. Sketch of the test area showing the rebar mesh, a polystyrene wedge on the lower left (blue) and the three honeycomb locations (red) in measurement area.

On the lower left side of the measurement area an inclined section of varying thickness has been realized by embedding a polystyrene wedge. This section has been excluded from the data throughout this study.

2.1 Feature extraction

Despite their frequent occurrence, honeycombs are hardly detectable with common NDT techniques [9,13,14,15,16]. That is because the cavities are mostly too small to be resolved. Still they significantly influence the concrete's properties. We extracted features from the three test methods. We define features as the most prominent signature in a sensor's signal indicating the presence of a particular defect.

As the IE feature we considered the peak resonance frequencies spectrum width by calculating the Q-factor. It can be regarded as an attenuation measure [17]. For US testing we considered the inverted amplitudes at the presumed back wall. The extracted feature from the GPR data is the

inverted amplitude variations just above the lower rebar mesh. Higher values indicate the potential presence of honeycombs for all three features. The extracted features are shown in figure 2. For more detail on the feature extraction please see [18].

The shown feature values in figure 2 correspond to the respective measurement area. They perform differently well on isolating the honeycomb locations. Nevertheless, none of the presented techniques is capable of unambiguous defect detection. Before proceeding to data fusion the features must be preprocessed. This includes co-registration, filtering and scaling as described in [18].

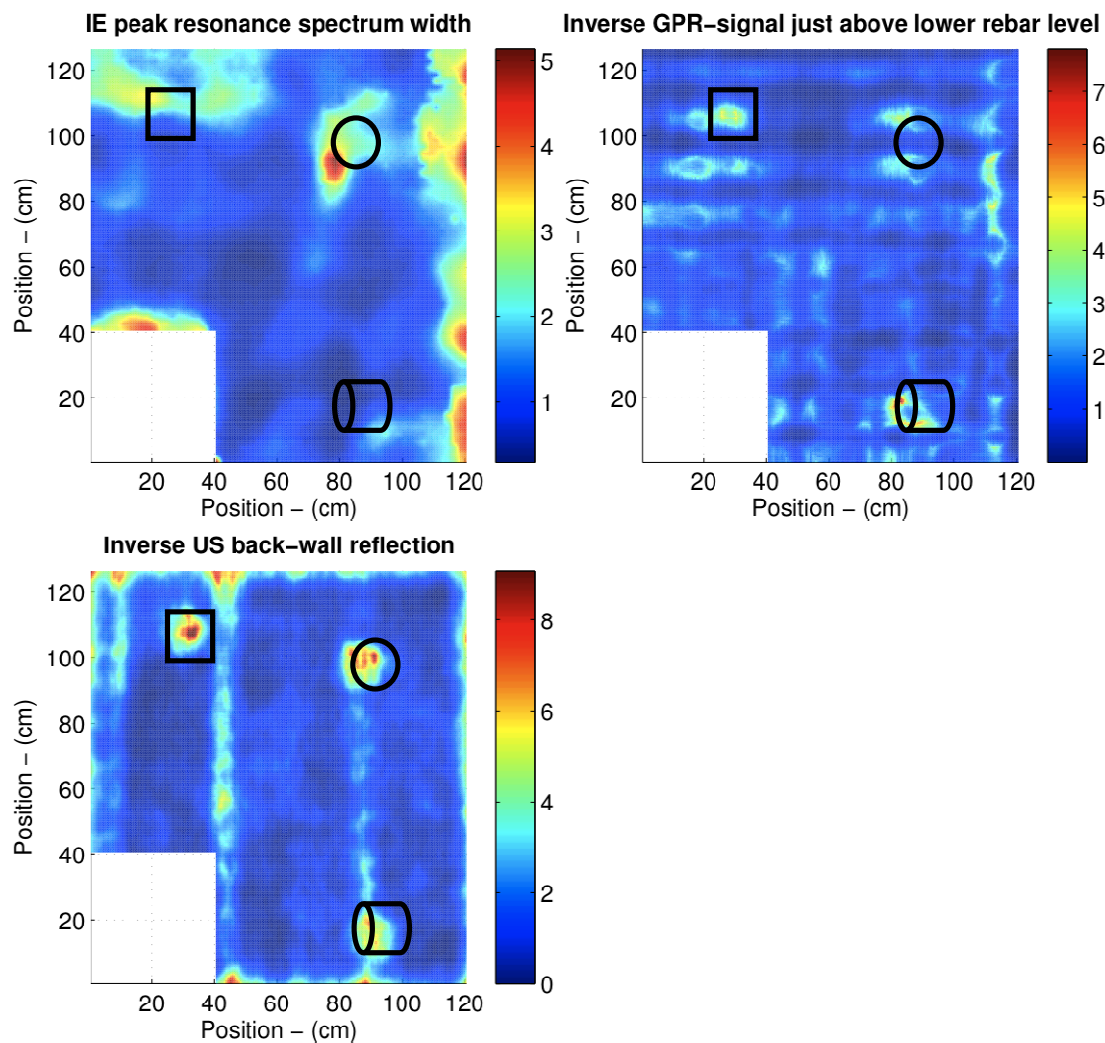


Figure 2. Feature set with marked honeycomb locations; upper left: Extracted feature from the IE test results: Q-factor of the peak thickness resonance frequencies; lower left: Extracted feature from the ultrasonic testing results: the pixel-wise inverted C-Scan at presumed back-wall; upper right: Extracted feature from the GPR data: pixel-wise inverted reflection amplitude just above the lower rebar level.

3 Data fusion and clustering

Data fusion techniques use redundancy and complementary data in order to enhance the information quality and to achieve a higher degree of certainty [19,20,21]. Even the inclusion of low significance data can contribute to the overall fusion result.

For the data fusion the feature set is transformed to feature space (FS) representation, a n -dimensional vector space in which each point is represented by the individual feature value at one measurement position. This allows the joint representation of all features in one mathematical space. Clustering algorithms group data points in FS based on a predetermined similarity measure. The ideal outcome in a NDT context would be to segregate defect and non-defect points. When projected back in spatial representation the defective areas can be isolated. We conducted three clustering algorithms to our data set, namely: K-Means [22] and Fuzzy C-Means [23] clustering as well as DBSCAN [24].

3.1 K-Means and Fuzzy C-Means clustering algorithm

Due to their simplicity in concept and implementation, K-Means and fuzzy C-Means clustering are frequently used for data analysis in NDT (e.g., [25,26,27]). They iteratively optimize the shape of clusters in FS by moving a predetermined number of randomly initiated points (centroids) in the center of mass of the closest FS-elements. While K-Means only allows the assignment of each FS element to one cluster, Fuzzy C-Means introduces ambiguous assignments of elements to multiple clusters with a certain membership degree. The clustering result for both algorithms is shown in figure 3.

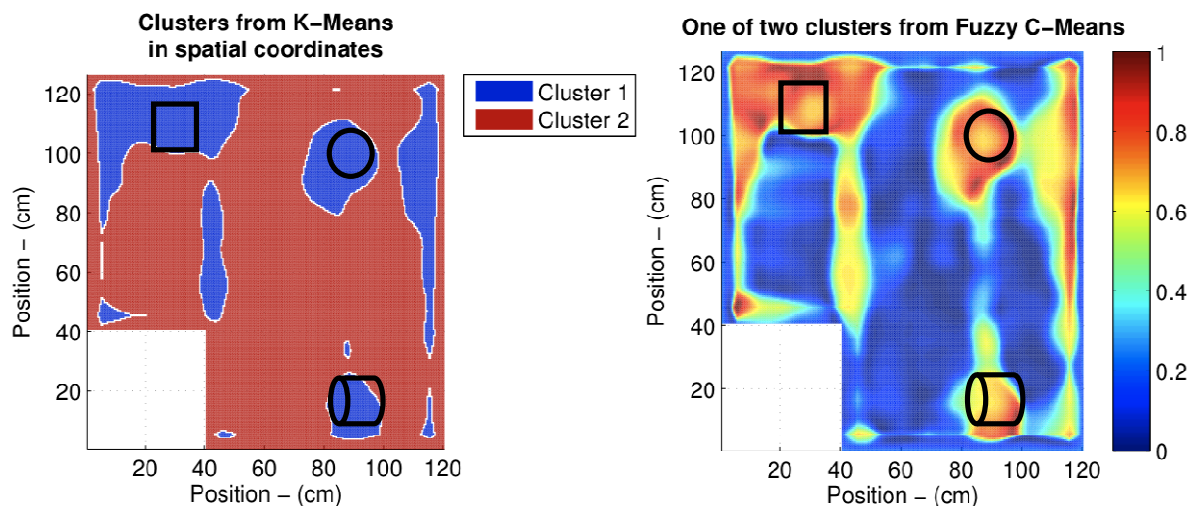


Figure 3. Clustering result from K-Means and Fuzzy C-means clustering; left K-Means clustering results for UT-GPR-IE dataset projected on 2D spatial coordinates with marked honeycomb locations; right: One cluster from Fuzzy C-Means for UT-GPR-IE dataset projected on 2D spatial coordinates with marked honeycomb locations.

The clustering outcome in figure 3 is qualitatively inaccurate for both techniques. Although the membership degree from Fuzzy C-Means seems to allow better separation between honeycombs and surrounding medium, it is still not satisfactory.

3.2 Density based clustering algorithm DBSCAN

The principle of DBSCAN is utterly different: the clustering is based on dense element neighborhoods in FS. Density is defined by a minimum number of neighboring elements within a given radius. Based on that, DBSCAN outputs the classification into densely connected elements (“core” and “border”) and outlier elements (“noise”). The number of clusters as well as their shape is not predefined and is found based on the discovered connectivity among accumulated elements. We filtered the clustering result by applying a spatial low pass filter to suppress scattered indications [28]. This further improves the result. In figure 4 the location of all three honeycombs is clearly isolated.

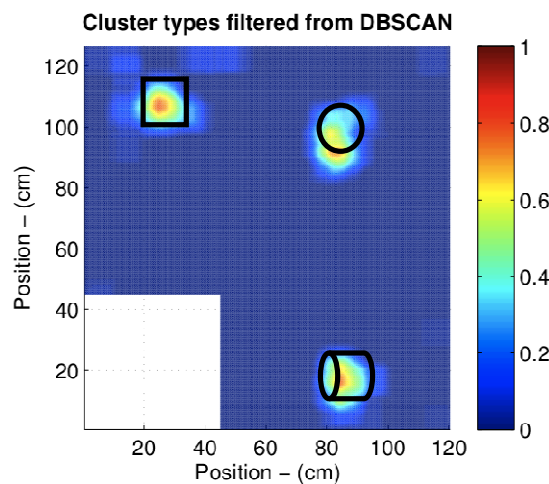


Figure 4. Low pass filtered DBSCAN clustering outcome for UT-IE-GPR dataset with marked honeycomb locations.

4 Evaluation of fusion results

The performance of the individual features vs. the fusion results is quantified by Receiver Operator Characteristic (ROC) curves. They illustrate the performance of binary classifier in dependence of a varying threshold [29]. The corresponding ratio of identified versus actual positives (defects) is plotted as the true positive rate (TPR) on the ordinate. The ratio of wrongly classified negatives is plotted as the false positive rate (FPR) on the abscissa. The resulting area under the curve (AUC) may be used as a benchmark. Alternatively, the FPRs at a fixed TPR may be used as in [30]. The ROC curves for the individual features as well as the clustering results are shown in figure 5. Since K-Means output is binary, its ROC is only representable as a point with no associated AUC value.

US performs best among the features in terms of the steepest curve and the largest AUC value (see figure 5). The clustering results should therefore be compared against US.

The best classification was accomplished by DBSCAN. At a TPR of 0.5, the FPRs for DBSCAN, US and Fuzzy C-Means are 0.000, 0.006 and 0.071 respectively. C-Means and K-Means clustering performed poorly. The Fuzzy C-means algorithm performed slightly better by virtue of the fuzzy membership degrees. Density based clustering on the other hand delivered superior results.

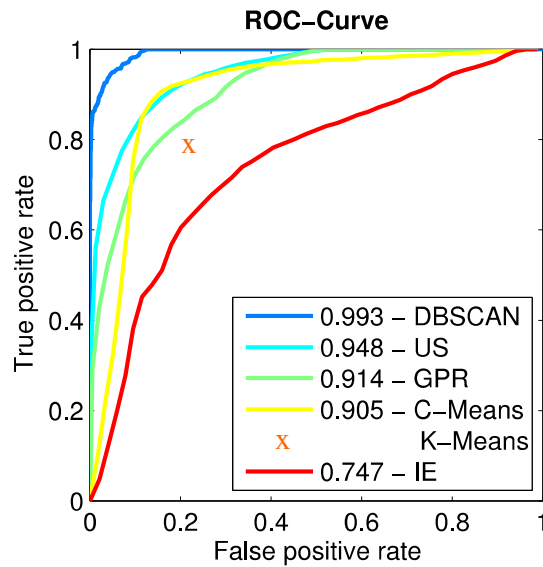


Figure 5. Receiver operating characteristic (ROC) curves for individual features and clustering approaches. Area under the curve (AUC) values are noted in the legend.

5 Acknowledgement

We greatly acknowledge the generous financial support provided by the Indio German Science and Technology Centre (IGSTC) through DLR (German Aerospace Center), (Grant no. 01DQ12088A). The authors are thankful to their colleagues Jens Wöstmann and Rüdiger Feldmann for their assistance in data collection and René Heideklang for the helpful discussions.

6 References

- [1] N. Gucunski, F. A. Romero, P. Shokouhi, and J. Makresias, "Complementary Impact Echo and Ground Penetrating Radar Evaluation of Bridge Decks on I-84 Interchange in Connecticut", Austin Texas, 2005.
- [2] A. Taffe, A. Gardei, M. Krause, C. Maierhofer, and H. Wiggerhauser, "Automatisierung zerstörungsfreier Prüfverfahren für das Bauwesen", *Materialprüfung*, vol. 46, no. 7-8, pp. 397-403, Juli 2004.
- [3] K. Reichling et al., "BETOSCAN – Robot controlled non-destructive diagnosis of reinforced concrete decks", in *7th International Symposium on Non Destructive testing in Civil Engineering proceedings*, Nantes, France, pp. 425-432, 2009.
- [4] J. HOŁA and K. Schabowicz, "State-of-the-art non-destructive methods for diagnostic testing of building structures – anticipated development trends", *Archives of Civil and Mechanical Engineering*, no. Volume 10, Issue 3, pp. 5–18, 2010.
- [5] N. Gucunski, A. Maher, and H. Ghasemi, "Condition assessment of concrete bridge decks using a fully autonomous robotic NDE platform", *Bridge Structures*, no. 9, pp. 123-130, 2013.

- [6] Bahdor Khalegie, Alaa Khamis, Fakhreddine O. Karray, and Saiedeh N. Razavi, "Multisensor data fusion: A review of the state-of-the-art," *Information Fusion*, vol. 14, pp. 28-44, 2013.
- [7] H. B. Mitchell, *Data Fusion: "Concepts and Ideas"*, Israel: Springer Heidelberg New York Dordrecht London, 2012.
- [8] Herbert Wiggensauser and Alexander Taffe, "NDT in Civil Engineering: Research, Application, Validation and Training", in *18th World Conference on Nondestructive Testing*, Durban, South Africa, 2012.
- [9] H. Wiggensauser, "Advanced NDT methods for the assessment of concrete structures", in *7th International Symposium on Non Destructive testing in Civil Engineering proceedings*, Nantes, France, 2009.
- [10] J. Blitz, "Ultrasonic Methods of Non-destructive Testing", Netherlands: Springer, 1995.
- [11] Mary J. Sansalone and William B. Streett, "Impact-Echo: Nondestructive Evaluation of Concrete and Masonry", Bullbrier Press, 1997.
- [12] Harry M. Jol, "Ground Penetrating Radar Theory and Applications", Amsterdam, Netherlands: Elsevier Science BV, 2009.
- [13] Ralf Beutel et al., "Comparative Performance Tests and Validation of NDT Methods", *Nondestructive Evaluation*, pp. 59-65, June 2008.
- [14] Allen G. Davis, "The nondestructive impulse response test in North America: 1985-2001", *NDT&E international*, vol. 36, pp. 185-193, 2003.
- [15] John H. Bungey, Michael G. Grantham, and Stephen Millard, "Testing of Concrete in Structures: Fourth Edition", New York: CRC Press, 2006.
- [16] Harald S. Müller, Martin Fenchel, Herbert Wiggensauser, and Chrsitiane Maierhofer , "Zerstörungsfreie Ortung von Gefügestörungen im Beton", 2009.
- [17] William M. Siebert, "Circuits, Signals, and Systems", Cambridge USA: MIT Press, 1985.
- [18] Christoph Völker and Parisa Shokouhi, "Multi sensor data fusion approach for automatic Honeycomb detection in concrete", Submitted to *NDT&E*, 2015.
- [19] Giacomo Della Riccia, Hans Joachim Lenz, and Rudolf Kruse, "Data Fusion and perception", CISM, Udine, Italy: Springer-Verlag Wien New York, 2001.
- [20] Xavier E. Gros, "NDT Data Fusion", Norwell, Massachusetts: Kluwer Academic Publishers, 1996.

- [21] Marie Aude Ploix, Vincent Garnier, Denys Breysse, and Joseph Moysan, "NDE data fusion to improve the evaluation of concrete structures", *NDT&E International*, pp. 442-448, April 2011.
- [22] J.B. MacQueen, "Some Methods for Classification and Analysis of MultiVariate Observations", in *Proc. of the fifth Berkeley Symposium on Mathematical Statistics and Probability*, Los Angeles, 1967, pp. 281-297.
- [23] J.C. Bezdek, "Pattern recognition with fuzzy objective function algorithms", Norwell USA: Kluwer Academic Publishers, 1981.
- [24] Martin Ester, Hans Peter Kriegel, Jörg Sander, and Xiaowei Xu, "A density-based algorithm for discovering clusters in large spatial databases with noise", in *Proceedings of the Second International Conference on Knowledge Discovery and Data Mining (KDD-96)*, Portland, Oregon, USA, 1996, pp. 226-231.
- [25] N. Godin, S. Huguet, R. Gaertner, and L Salmon, "Clustering of acoustic emission signals collected during tensile tests on unidirectional glass/polyester composite using supervised and unsupervised classifiers", *NDT & E International*, vol. 37, no. 4, pp. 253-264, 2004.
- [26] Jaejoon Kim, Guang Yang, Lalita Udpa, and Satish Udpa, "Classification of pulsed eddy current GMR data on aircraft structures", *NDT & E International*, vol. 43, no. 2, pp. 141-144, 2010.
- [27] Saleh Hosseini and Aouni A. Lakis, "Application of time–frequency analysis for automatic hidden corrosion detection in a multilayer aluminum structure using pulsed eddy current", *NDT & E International*, vol. 47, no. 1, pp. 70-79, 2012.
- [28] Paul Mather and Magaly Koch, "Computer Processing of Remotely-Sensed Images: An Introduction", West Sussex, UK: Wiley Blsckwell, 2011.
- [29] J.A. Swets, "Signal Detection Theory and Roc Analysis in Psychology and Diagnostics: Collected Papers", Mahwah, New Jersey: Lawrence Erlbaum Associates, 1996.
- [30] René Heideklang and Parisa Shokouhi, "Multi-sensor image fusion at signal level for improved near-surface crack detection", *NDT & E International*, vol. 71, pp. 16-22, 2015.