Available online at www.sciencedirect.com
ScienceDirect
NDT&E International 41 (2008) 163–168
NDT&E international
www.elsevier.com/locate/ndteint

A cost effective development of an ultrasonic A-scans database for high-temperature hydrogen attack

Ahmed Yamani*

KFUPM, P.O. Box 1811, Dhahran 31261, Saudi Arabia

Received 6 December 2006; received in revised form 11 June 2007; accepted 12 October 2007
Available online 18 October 2007

Abstract

Successful application of the rich collection of classification algorithms to non-destructive testing signals depends heavily on the availability of adequate and representative sets of training examples, whose acquisition can often be very expensive and time consuming. In this paper, an out-of-service pressure vessel known to have lots of high-temperature hydrogen attack defects is used to develop in a cost effective manner a database of ultrasonic A-scan signals. To test how adequate and representative these sets of A-scan signals are, a basic feature extraction method coupled with a primitive classifier is shown to distinguish accurately the hydrogen attack from geometrically similar defects.

Keywords: Hydrogen attack; A-scan; Database; Classification; Feature extraction

1. Introduction

Studies have shown that manual ultrasonic inspection can be accurate but highly variable, depending on the inspection skills, training and emotional status or fatigue of the inspectors [1]. Many inaccurate inspections result from faulty instrument calibrations, inaccurate probe selection, or inaccurate interpretation of inspection results. The human factor when combined with variations in instrumentation, contribute to a lack of consistency in inspection results and interpretations.

Considerable advancement in research and development in the last few decades has enabled non-destructive testing (NDT) to change from a "Black Smith" profession to an advanced multidisciplinary engineering profession. This has led to cost effective solutions of many challenging problems. Pipelines for instance, can now be screened without disturbing the production using intelligent tools such as pigging [2], guided wave ultrasound [3], phased arrays [4], etc.

In addition, the existence of cheap computing capabilities has led to the development of NDT techniques that are operator independent. These techniques rely heavily on the collection of huge measurement data that after appropriate processing will enhance operator interpretation. Automated ultrasonic detection and classification (AUDC) systems are thus becoming increasingly popular [5]. Motivation for the use of such systems arises from the need for accurate interpretation of large volumes of inspection data, and minimizing errors due to human factors. AUDC systems consists of three major parts namely pre-processing, features extraction, and classification. A number of supervised and unsupervised classification algorithms [6] such as K-mean clustering algorithm, fuzzy C-means, and more recently neural networks have been proposed for classifying signals. Using a suitable training algorithm, these networks can be trained to learn the correlation between features in signals and the type of reflector. However, the success of all such algorithms depends heavily on the availability of an adequate and representative set of training examples, whose acquisition is often very expensive and can be time consuming. For instance, application of ultrasonic techniques for high-temperature hydrogen attack (HTHA) detection [7–9] requires a skilled ultrasonic technician with a good understanding of the mechanism of HTHA, and the ways it affects the propagation and

*Tel.: +966 38602463; fax: +966 38603535.
E-mail address: myamani@kfupm.edu.sa

0963-8695/$ - see front matter
doi:10.1016/j.ndteint.2007.10.007

scattering of the ultrasonic wave. There have been cases in the industry where NDT inspectors have either missed HTHA or called it incorrectly [9].

The objective of this contribution is to create a reliable database for HTHA from a retired pressure vessel known to have many HTHA defects [11], and to show that advanced signal processing techniques can aid NDT technicians to correctly identify HTHA from similar defects found in steels.

2. High-temperature hydrogen attack

HTHA is a metal degradation phenomenon that is well known to occur in carbon and low steels exposed to high partial pressure of hydrogen at elevated temperature. The source of hydrogen is the hydrocarbons in the flow steam. The damage is caused by the seepage of hydrogen that reacts with metal carbides to form methane gas. This reaction decarburizes steel, produces microcracks, and lowers the toughness of steel without necessarily producing a loss of thickeness.

Detection of HTHA is important to assure safe operation of pressure vessels and piping systems susceptible to such damage. Application of ultrasonic techniques for the detection of HTHA [7–9] requires high-skilled technician with a good understanding of the mechanism of HTHA and how it affects the propagation and the scattering of ultrasonic waves. While hydrogen attack affects wave velocity ratio, backscattered amplitude, and the frequency of the ultrasonic signal, other material discontinuities can influence these ultrasonic parameters as well and give a false call. For example, microcracks, voids, inclusions, and grains in the material scatter ultrasound and have frequency dependant affects. In addition, stringers in steel; which are non-metallic inclusions in the original ingot, become elongated though the rolling process and form into long, continuous or semi-continuous inclusions. Thus, ultrasonic reflections from these stringers can be easily misinterpreted as HTHA especially when they are close to the inner diameter surface. There have been cases in the industry where inspectors have either missed HTHA or called it incorrectly [9]. Ultrasonic testing for this application is therefore not straightforward and requires a logical test methodology to detect HTHA. In the next section, a complete description of the data acquisition of ultrasonic A-scans obtained from a retired pressure vessel known to have many HTHA will be outlined.

3. Data collection and database creation

An out-of-service pressure vessel with wall thickness 33 mm known to have many HTHA [11] is used to collect RF A-scan signals for use in the database. The data acquisition system used is shown in Fig. 1. It consists of a SONATEST Masterscan 340 flaw detector, compression wave probes, couplant, and calibration blocks. The flaw

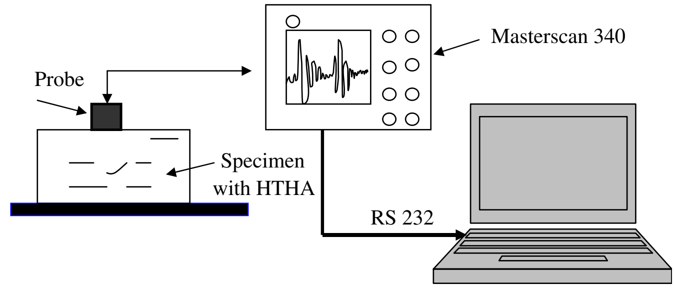

Fig. 1. A block diagram representing the data acquisition system used.

Fig. 2. Out-of-service pressure vessel used to collect the data.

detector has the capability of displaying and storing up to 100 RF A-scan signals. It also can transfer these signals to a PC via an RS 232 interface using the SONATEST Data Management Software (SDMS).

A 4 MHz single compression probe (SLH4-10) is connected to the flaw detector operating in a pulse-echo mode. First, an I.I.W. A2 calibration block is used to calibrate the instrument in the RF mode. The range is set at 50 mm of steel; the probe is placed on the top of the A2 block (2 in. or 25.4 mm thickness). The speed knob and the delay button are used to get two equidistant backwall reflections. Next, the sensitivity and gain settings are carried out using a 1.5 mm hole in the A2 calibration block. Second, the range is reduced to 35 mm and a delay of 38.10 mm is applied to the flaw detector so that one wall thickness is displayed across the screen. Next, the probe is placed on the outer wall of the 33 mm pressure vessel shown in Fig. 2. A snapshot of the flaw detector screen is shown in Fig. 3, where five HTHA defects are shown to be distributed along the pressure vessel wall thickness. The cursor available in the SDMS software is used to measure accurately the location of the maxima of the RF signals displayed. Thus, the defects are found to be located from the outer-diameter surface at distances 3.66, 11.68, 15.69, 18.57, and 23.89 mm, respectively. The thicker horizontal line in the graph represents a gate that starts from

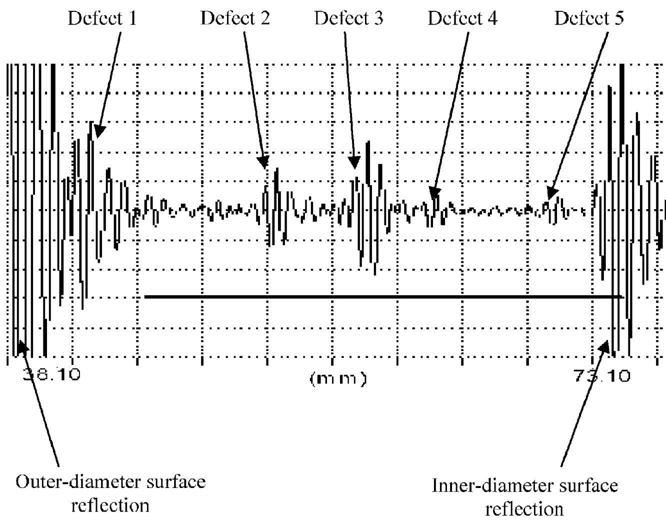

Fig. 3. Snapshot of the flaw detector screen showing five HTHA defects.

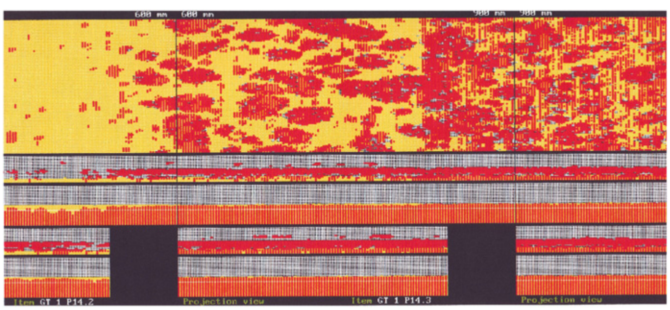

Fig. 4. A C-scan sample of the pressure vessel showing HTHA in its critical stage of "connection".

45.38 mm (7.28 mm from the outer-diameter surface) and ends at 70.16 mm (32.06 mm from the outer-diameter surface). Fig. 4 shows a C-scan sample obtained during the inspection of the pressure vessel. It clearly shows that HTHA defects are in the critical stage of "connection" where rupture would occur imminently.

Since the A-scan signal of only one defect is of interest for the creation of the database, and that HTHA defects are usually close to the inner diameter surface, defect 5 is considered for this task.

Zooming on the region around the position of defect 5 (reducing the range to 10 mm, and tuning the delay), so that the signal of defect 5 is displayed across the screen. The probe is moved around to maximize the pulse echo of defect 5. Fig. 5 shows a snapshot of the flaw detector screen showing the pulse echo of defect 5. The location of this defect is displayed at 61.19 mm corresponding to 23.09 mm from the outer-diameter surface (61.19–38.10). This confirms the closeness of defect 5 to the inner surface.

The probe is now moved randomly around defect 5 to record as many A-scan signals as possible. These acquired signals would be obtained by different operators performing the test. Statistically speaking, no two operators would measure the same A-scan for a given defect. Next, another HTHA defect is detected and all possible A-scan signals are

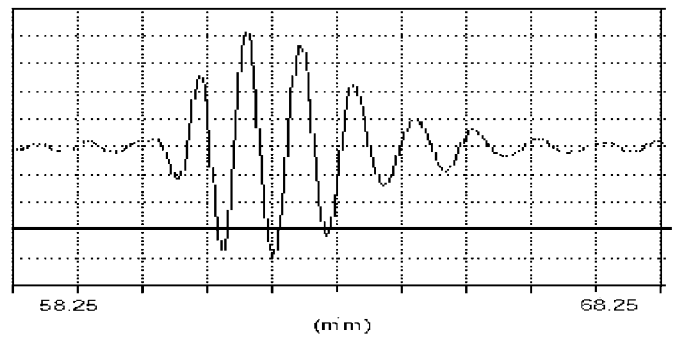

Fig. 5. Snapshot of the flaw detector screen showing defect 5 isolated from the rest of the defects.

recorded in a similar manner. This process is carried on, and each time the A-scan signals are transferred to a directory in the Laptop using the SDMS software to create a HTHA databank of 400 A-scan signals. The acquisition of such signals is carried out by the author himself to assure the adequacy and the representativeness of the data sets. This is reflected in the high classification accuracy obtained even when simple features and basic classifier are used. Thus, using a commercial flaw detector, simple feature extraction technique, and a basic classifier can serve as an automatic NDT tool that aids inspector to accurately detect HTHA from geometrically similar defects.

4. Experimentation

To test the adequacy and the representativeness of the developed HTHA database, two other databases of geometrically similar defects are created. These defects are lamination (LAM), and an artificial defect that consists of a flat-bottom hole (FBH). The AUDC system to be used consists of three major parts:

(a) a pre-processor,
(b) a feature extractor, and
(c) a basic classifier.

Basic pre-processing operation is applied to the A-scan signals. It consists of removing the DC components, and normalizing all the signals to have the same energy. The feature extraction stage here is based on the principal component analysis (PCA) technique [10]. PCA is used abundantly in all forms of analysis that range from neuroscience to computer graphics. This technique is a simple and a non-parametric method of extracting relevant information from confusing data sets. With minimal additional effort, PCA provides a roadmap for reducing a complex data set to a lower dimension in order to reveal the hidden, simplified structure that often underlie it. This hidden information is called feature. Next, the extracted features are presented to a priori trained classifier based on nearest-neighbor classification to decide on which class the inputted A-scan signal belongs to.

4.1. Data organization and processing

Fig. 6 shows one defect database organized in four sub-groups SG1, SG2, SG3, and SG4. The 100 A-scan signals contained in each sub-group are collected during one visit to the site. Each sub-group data set is thus collected in different conditions and at different times. A training vector $X_{i,j}^{Tr}$ containing 20 A-scan signals picked up randomly from sub-group i of database j. Similarly, a testing vector $X_{i,j}^{Te}$ containing 10 A-scans signals picked up randomly from the remaining 80 A-scan signals of the ith sub-group, belonging to database j. Thus, a training matrix for the ith sub-group of the three defects is formed as

$$\mathrm{Tr}_i = [X_{i,1}^{Tr} X_{i,2}^{Tr} X_{i,3}^{Tr}] \tag{1}$$

Similarly, a testing matrix of the ith sub-group of the three defects is formed as

$$\mathrm{Te}_i = [X_{i,1}^{Te} X_{i,2}^{Te} X_{i,3}^{Te}] \tag{2}$$

The AUDC system is first trained using the training matrix Tr_i and tested using the testing matrix Te_i.

4.2. Evaluation

To evaluate the performance of such system, it is assumed that once the system is trained, an operator goes on site and performs a test that consists of 10 measurements for each defect class and presents these signals to the AUDC system for classification. This operation can be repeated as much as needed. Since the testing matrix is picked up randomly (10 out of 80), and since it is not probable that any two operators can measure the same A-scan, then $\binom{80}{10} \approx 1.6 \times 10^{12}$ independent tests are possible. For each test (30 A-scan measurements for three classes), the AUDC outputs a confusion matrix that measures the classification accuracy. After 500 independent tests, the worst result obtained is shown in Table 1. From this, it can be seen for instance that out of 10 measurements, the LAM defect is detected and identified nine times and missed once for the FBH. Similarly, the HTHA defect is detected and identified seven times and missed twice for LAM, and once for FBH defect. Alternatively, it can be seen that LAM and FBH have 90% classification accuracy, whereas, HTHA has only 70% classification accuracy. The overall classification accuracy can be obtained by averaging the diagonal elements. Here 83.33% is obtained.

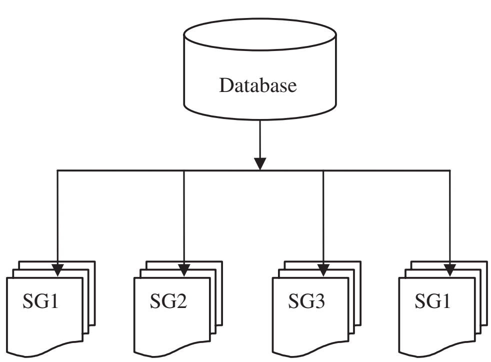

Fig. 6. Organization of each database in four sub-groups of 100 scans each.

Table 1
Worst confusion matrix result obtained after 500 tests

Worst test		Classified as		
		LAM	HTHA	FBH
True class	LAM	9	0	1
	HTHA	2	7	1
	FBH	1	0	9

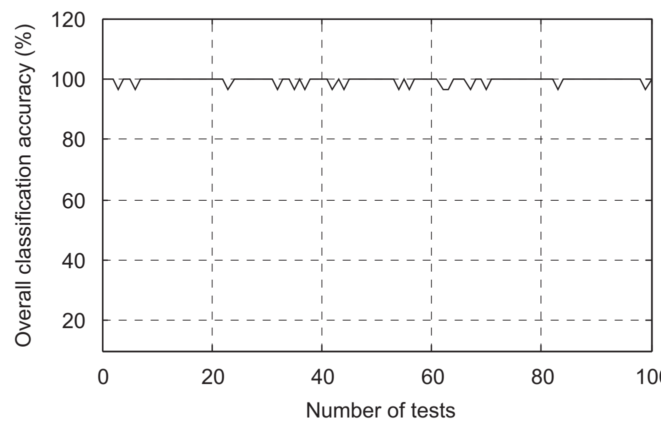

Fig. 7. Overall classification accuracy for the three defects (average 99.46%).

The overall classification accuracy (average of the diagonal elements of the confusion matrix) is not affected much when the system is subjected to different tests. For 100 independent tests, the overall classification accuracy is shown in Fig. 7. The average over these tests is 99.46%. For HTHA defect, the classification accuracy versus the number of tests is shown in Fig. 8, which averages to 98.4%.

The above results are obtained by fine tuning the feature extraction process. As the magnitude of the principal components decay almost exponentially, only the first 10 components are taken as features and fed to the classifier. The 10th PC represents 0.54% of the first PC as shown in Table 2.

Next, the classification accuracy of defects is investigated when the number of PCs taken as features is increased. Although the magnitude of the PC decreases rapidly (Table 2), it seems from Fig. 9 that increasing the number of features will decrease the classification accuracy. These implies that the first few PCs represent characteristic features for each defect and that other subsequent PCs carry similar defect information and thus, contribute to the confusion of the classifier. The high classification accuracy obtained earlier (Figs. 7 and 8) was obtained with optimal feature selection.

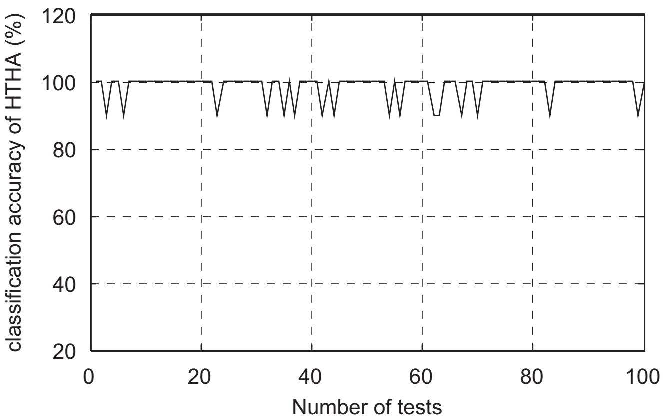

Fig. 8. Classification accuracy for the HTHA (average = 98.4%).

Table 2
Magnitude of the first 10 PCs fed to the classifier

PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10
875.1	408.9	180.2	35	31	14.5	10.7	7.4	6.5	4.7

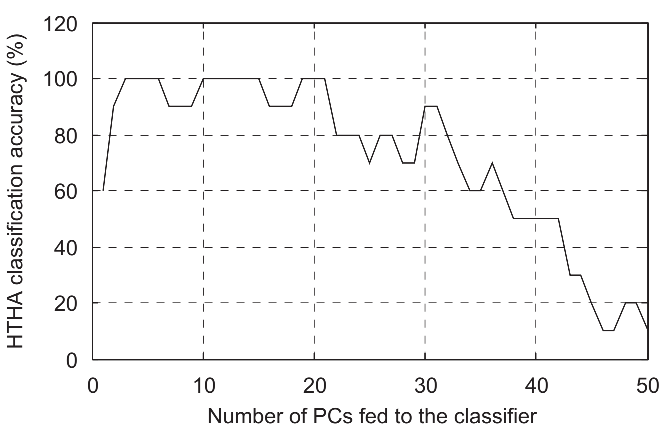

Fig. 9. Classification accuracy for HTHA versus number of PCs taken.

Table 3
Effect of the sub-group data on the classification accuracy for HTHA for different number of tests

HTHA	Number of tests		
	10	20	40
SG1 (%)	91	90.5	90.3
SG2 (%)	98	98.5	98
SG3 (%)	94	94	97
SG4 (%)	97	96	97.3

Finally, the effect of sub-group data is used to investigate the classification accuracy. Table 3 shows the consistency of the high classification accuracy for HTHA when all the sub-groups are used to pick up randomly the training and the testing matrices. It can be seen from this Table that the number of tests does not affect the classification accuracy. However, the sub-group data shows some variance in the accuracy. It is believed that this is due to many factors including the quality of each sub-group data collection.

5. Conclusion

Ultrasonic detection of HTHA requires a skilled ultrasonic technician with a good understanding of the mechanism of HTHA, and the ways it affects the propagation and scattering of the ultrasonic wave. Automatic detection of such defect requires the availability of an adequate and representative set of training examples whose acquisition is usually time consuming and can be very expensive. In this contribution, it is shown that with a commercial flaw detector, a reliable database can be created. HTHA is accurately classified among geometrically similar defects using simple feature extraction technique coupled with a primitive classifier. Thus, it is shown that the availability of reliable database is vital for any AUDC system to give accurate results that can aid unskilled NDT operator to distinguish between challenging defects such as HTHA and defects such as stringers commonly found in pressure vessel and piping systems.

Acknowledgments

This research is funded by King Abdul-Aziz, City of Science and Technology (KACST), under AR 24-106. The author would like to thank KFUPM for providing the facilities to carry out such research. The author is also grateful to Mr. Fathi Al-Qadeeb from the inspection department of Saudi ARAMCO for facilitating the data acquisition.

References

[1] Alippi A, Mayer WG, editors. Ultrasonic methods in evaluation of inhomogeneous materials. NATO ASI series, series E: applied sciences, no. 126. Dordrecht: Martinus Nijhoff Publishers; 1987.
[2] Dauby F. Numerous lessons learned when intelligent pigging is attempted on 60-year-old gas pipeline. Pipeline Gas J 2005;232(10): 44–8. 49–52.
[3] Alleyne DN, Pavlakovic B, Lowe MJS, Cawley P. Rapid, long range inspection of chemical plant pipework using guided waves. In: AIP conference proceedings, vol. 557, April 30, 2001. p. 180–7.
[4] Smith RA, Bending JM, Jones LD, Jarman TRC, Lines DIA. Rapid ultrasonic inspection of ageing aircraft. Insight-Nondestr Test Cond Monit 2003;45(3):174–7.
[5] Polikar R, Udpa L, Udpa S, Honavar V. An incremental learning algorithm with confidence estimation for automated identification of NDE signals. IEEE Trans UFFC 2004;51(8):990–1001.
[6] Anastassopoulos AA, Nikolaidis VN, Philippidis TP. A comparative study of pattern recognition algorithms for classification of ultrasonic signals. Neural Netw Appl 1999;8:53–66.
[7] Birring AS, Kawano K. Ultrasonic detection of hydrogen attack in steels. Corrosion 1989:259–63.

[8] Birring, AS, Elliot J, Hsiao CP. Detection of hydrogen attack in base metal and weld HAZ. In: Proceedings of the ASME pressure vessel and piping conference, 1995.
[9] Birring AS, Riethmuller M, Kawano K. Ultrasonic techniques for detection of high temperature hydrogen attack. Mater Eval 2005:110–5.
[10] Shlens J. A tutorial on principal component analysis. Internal report, Institute of Nonlinear Science, University of California, San Diego, La Jolla, Ver. 2, December 2005, p. 1–13.
[11] Al-Qadeeb FE, Miller SD. NDT characterization of HIC in pressure vessels. Saudi ARAMCO engineering report SAER no. 5869, Technology program final report, ITEM ID-01/97-T, January 2003.