4th Middle East NDT Conference and Exhibition, Kingdom of Bahrain, Dec 2007
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Automatic Detection of High Temperature Hydrogen Attack defects from Ultrasonic A-scan Signals.

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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 attach (HTHA) 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.**

Index Terms **— Nondestructive testing, signal processing, classification, feature extraction, ultrasonic A-scan database, hydrogen attack.**

I. INTRODUCTION

Considerable advancement in research and development in the last few decades has enabled nondestructive 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, guided wave ultrasound, phased arrays [1], etc…
In addition, the existence of cheap computing capabilities has led to the development of NDT techniques that rely heavily on the collection and processing of huge measurement data that eventually enhance operator interpretation. Automated ultrasonic detection and classification (AUDC) systems are thus becoming increasingly popular. 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 consist of three major parts namely pre-processing, features extraction, and classification. A number of supervised and unsupervised classification algorithms [2] such as K-mean clustering algorithm, fuzzy C-means, and more recently neural networks have been proposed for classifying signals. Using a suitable 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. training algorithm, these networks can be trained to learn the correlation between features in signals and the For instance, application of ultrasonic techniques for high temperature hydrogen attack (HTHA) detection [3] 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.

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

II. 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 [3] 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.

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.

III. DATABASE CREATION

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

The flaw detector has the capability of displaying and storing up to 100 RF A-scan signals. It also can transfer these signal to a PC via an RS 232 interface using the SONATEST Data Management Software (SDMS). After calibrating the flaw detector, the probe is placed on the outer wall of the 33 mm pressure vessel. A snapshot of the flaw detector screen is shown in Figure 1, where 5 HTHA defects are shown to be located within the pressure vessel wall thickness.

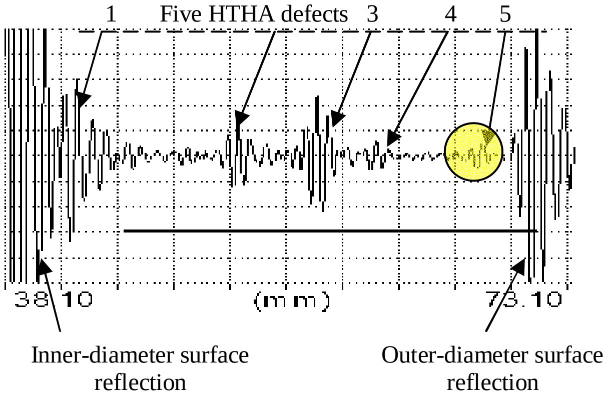

Figure 1: Snapshot of the flaw detector screen showing 5 HTHA defects located along the wall thickness.

The time-base of the flaw detector is zoomed to the region of defect 5 to isolate its A-scan signal from the rest of the defects. The result is shown in Figure 2. The probe is now moved randomly around the detected defect to record as many A-scan signals as possible to cover all possible measurements that can be obtained for this defect when different operators are performing the test. Next, another HTHA defect is detected and all possible A-scan signals are 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.

To test the adequacy and the representativeness of the developed HTHA database, two other 400-A-scans Databases of geometrically similar defects are created. These defects are lamination (LAM), and an artificial defect that consists of a flat-bottom hole (FBH).

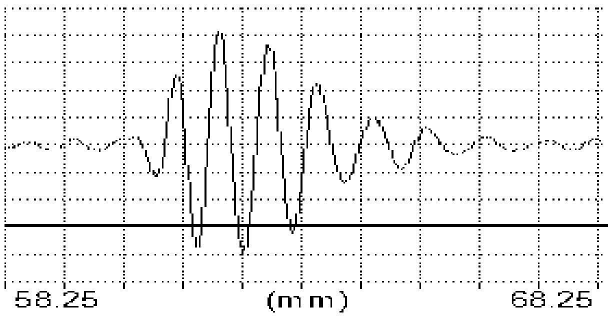

Figure 2: A snapshot of the flaw detector screen showing one HTHA defect

IV. TESTS

The pre-processing stage here consists of removing the DC components, and normalizing all the signals to have the same energy. The feature extraction stage is based on the principal component analysis (PCA) technique [10]. Next, the extracted features are presented to a priori trained classifier based on nearest-neighbor criterion to decide on which class the inputted A-scan signal belongs to. The databases are organized in 4 sub-groups containing 100 A-scans each. The AUDC system is first trained using 20 sets of A-scan for each class, and then tested by a set of 10 A-scans. The training sets are therefore picked randomly from each sub-group, whereas, the testing sets are picked randomly out of the 80 remaining sets. This results in appreciatively 1.6×10^{12} independent possible tests. The AUDC system is tested 500 times and the worst classification result is shown in the confusion matrix shown in Table I below.

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

Table I: Worst confusion matrix after 500 tests.

The worst case scenario is that for instance, out of 10 measurements, the lamination defect is detected and identified 9 times and missed once for the FBH. The average classification accuracy (average along the matrix diagonal) is 83.3%. For the 500 tests, the average classification accuracy for the HTHA is 99.46%.

V. CONCLUSION

VI.

It has been shown that HTHA defects can be distinguished from geometrically similar defects if the AUDC system is trained by an adequate and representative set of data. The classification accuracy obtained for the HTHA is almost perfect.

ACKNOWLEDGEMENT

The authors wish to acknowledge the support of King Abdul-Aziz City of Science and Technology (KACST) Saudi Arabia, to carry this research.

REFERENCES

[1] Alippi, A. and Mayer, W. G. (Eds.) "Ultrasonic methods in evaluation of inhomogeneous materials, NATO ASI Series, Series E: Applied Sciences, no. 126, Martinus Nijhoff Publishers, Dordrecht, 1987

[2] Dauby, F. "Numerous lessons learned when Intelligent Pigging is attempted on 60-year-old gas pipeline" Pipeline & Gas Journal, vol. 232, no. 10, pp. 44, 48, 49-52, Oct. 2005.

[3] Alleyne, D.N., Pavlakovic, B., Lowe, M.J.S., and Cawley P., "Rapid, long range inspection of chemical plant pipework using guided waves", AIP Conference Proceedings, Volume 557, pp. 180-187, April 30, 2001.

[4] Smith, R. A., Bending, J. M., Jones, L. D., Jarman, T. R. C., and Lines, D. I. A. "Rapid ultrasonic inspection of ageing aircraft", Insight- Nondestructive testing and Condition Monitoring, Vol.45, no.3, pp. 174-177, March 2003.

[5] Polikar, R.,Udpa, L., Udpa, S., and Honavar, V., "An incremental learning algorithm with confidence estimation for automated identification of NDE signals", IEEE trans. UFFC, vol. 51, no. 8, pp. 990-1001, August 2004.

[6] Anastassopoulos, A.A., Nikolaidis, V.N., and Philippidis, T.P., " A comparative study of pattern recognition algorithms for classification of ultrasonic signals", Neural Net. & Applic., Vol. 8, pp.53-66, 1999.

[7] Birring A.S., Kawano, K., " Ultrasonic detection of hydrogen attack in steels", Corrosion, pp. 259-263, March 1989.

[8] Birring, A. S., Elliot, J. and Hsiao, C.P. " Detection of hydrogen attack in base metal and weld HAZ", ASME Pressure Vessel and Piping Conference, 1995.

[9] Birring, A.S., Riethmuller, M., and Kawano, K. " Ultrasonic techniques for detection of high temperature hydrogen attack", Material Evaluation, pp. 110-115, Feb. 2005.

[10] Shlens, J. " A Tutorial on Principal Component Analysis", Internal report, Institute of Nonlinear Science, Univ. Cal., San Diego La Jolla, Ver. 2, pp-1-13, Dec. 2005.