Title
Abductive signal interpretation for nondestructive evaluation

Authors
O'Rorke, Paul
Morris, Steven

Publication Date
1991-09-21

Peer reviewed

Abductive Signal Interpretation for Nondestructive Evaluation[1]

Paul O'Rorke[2] (ororke@ics.uci.edu)
Steven Morris (morris@ics.uci.edu)
Department of Information and Computer Science
University of California, Irvine, CA 92717
Phone: (714) 854-2894

September 21, 1991
TR 91-66

TOPICS: DIAGNOSIS,
MODEL-BASED REASONING,
INTELLIGENT PATTERN RECOGNITION

Abstract

This paper reports on one aspect of a collaborative project exploring applications of AI to Nondestructive Evaluation (NDE). The goal of NDE is to determine whether parts under evaluation are "good" or "defective" without damaging the parts. Piezoelectric probes are often used to produce ultrasonic signals that indicate the existence of cracks and other defects inside solid materials. This paper shows how knowledge-intensive explanatory reasoning can be used to construct an interpretation of the signals, simultaneously classifying the material under evaluation.

[1]Export Authority: 22 CFR 125.4(b) (13).

[2]Research supported in part by National Science Foundation grant number IRI-8813048, Douglas Aircraft Company, and the University of California MICRO Program.

Contents

List of Figures

1 Introduction

The goal of nondestructive evaluation (NDE) is to determine whether parts under evaluation are "good" or "defective" without damaging the parts. Piezoelectric probes are often used to produce ultrasonic signals that indicate the existence of cracks and other defects inside solid materials. Ultrasound is widely used to test materials during manufacturing and service. For example, aircraft manufacturers use NDE techniques during the production of aircraft and airline operators also employ NDE techniques to maintain and inspect their fleets in service.

In (Amirfathi, Morris, O'Rorke, Bond & St. Clair, 1991; O'Rorke, Morris, Amirfathi, Bond & St. Clair, 1991; St. Clair, Bond & Sabharwal, 1990), we reported on methods for applying techniques from AI research on learning and vision to NDE. These techniques were aimed at the automatic construction of systems associating symptoms observed in NDE signals with classifications of parts (e.g., "nominal" or "defective"). The resulting decision methods are subject to the well-known limitations of first generation expert systems (Partridge, 1987).

This paper presents an alternative (second generation) knowledge-based approach to the interpretation of signals resulting from nondestructive tests. The new approach uses knowledge about the physical situation including knowledge about the structure of the part being tested. This will enable the system to make distinctions currently made only by human NDE technicians.

2 Representing NDE Knowledge

The approach requires rules associating characteristics of observed NDE signals and physical scenarios with diagnoses. The first step is to determine the relevant knowledge to represent and a suitable representation language.

We want to talk about signals, signal sources and sinks (transducers). We need a language for discussing parts under evaluation (e.g., test blocks, their top surface, interior, bottom surface, cracks, etc.). Some knowledge of the physics of signal propagation is necessary. We also need a language for describing NDE signals qualitatively.

We illustrate the kind of knowledge and representation necessary for an abductive approach to NDE in terms of some test blocks used for calibrating ultrasonic probes. Figure 1 is a sketch of a testing scenario using a standard test block. In this pulse-echo "A-scan" testing scenario, a piezo-electric quartz transducer is used to send ultrasonic pulses into the block. The transducer is both signal source and sink; it sends and later receives pulses.

2.1 Geometry

In this paper, we describe a theory that covers a set of nine test blocks. Each block is an aluminum cylinder 2 inches in diameter. The blocks are different sizes, but each block has a 3/64 in. diameter hole extending 3/4 in. up from the bottom of the block. The top of the (air filled) hole simulates a crack. The hole is plugged with sealant (probably no more than 1/4 in.) to prevent corrosion. The block shown in figure 1 has a crack .25 inches deep (so the block is .75+.25=1.0 inches high).

The beam of sound is collimated and approximately 1/4 inch in diameter. Because of impedance mismatch at the crack, almost all sound energy incident on the crack (on the top of the hole) is reflected back to the transducer. Little or no energy is reflected back from the sealant. Some energy is reflected back from the bottom of the cylinder, however, since the transducer and the beam of sound are wider than the crack.

We can represent relevant geometrical features of the test block using facts:

```
depth_l(front(Block),0).
depth_l(back(block31,0.8125).
depth_l(back(block32,0.875).
depth_l(back(block33,1.0).
depth_l(back(block34,1.125).
depth_l(back(block35,1.25).
depth_l(back(block36,1.375).
depth_l(back(block37,1.5).
depth_l(back(block38,1.625).
depth_l(back(block39,1.75).
```

The first statement says that the front surfaces of all the test blocks are at depth zero. The remaining statements give the depths of particular test blocks. For example, block33 is one inch deep.[3] The depths of internal features (such as manufactured holes, known defects, etc.) could be specified similarly.

2.2 Signals

A NDE signal derived from a test block is shown in figure 2. Qualitative descriptions can be derived from this sort of NDE time-series data using techniques from machine vision. (See (O'Rorke, et al., 1991) for details.) An example is:

[3] So the crack is $1 - .75 = .25$ in. deep in block33. Note that the first two depths and cracks are 0.0625 in. apart but after that the depth increases in regular increments of 0.125 inches.

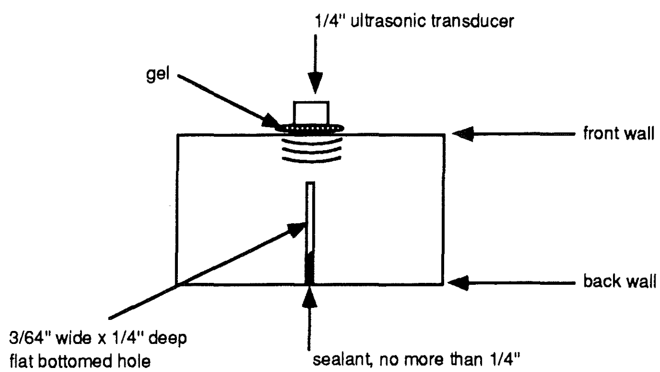

Figure 1: A Nondestructive Evaluation Scenario

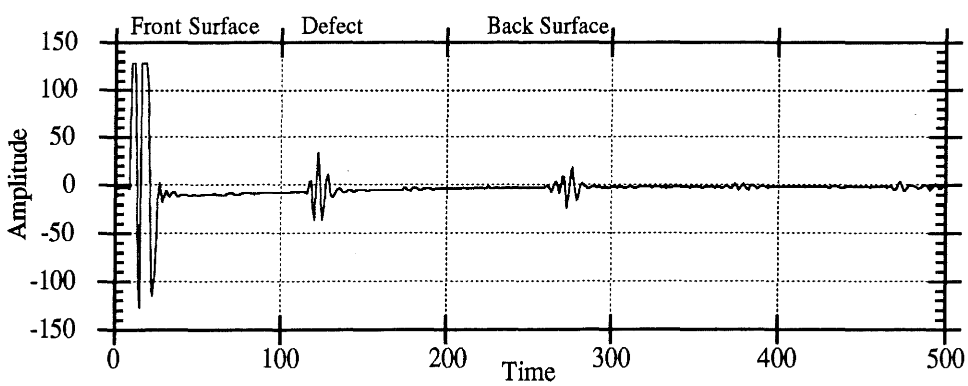

Figure 2: An NDE Signal

```
signal(d35,block35).
peaks(d35,3).
  peak(d35,1,d35p1).
    ptime(d35p1,13.5).
    amplitude(d35p1,115.26).
  peak(d35,2,d35p2).
    ptime(d35p1,116.5).
    amplitude(d35p1,14.33).
  peak(d35,3,d35p3).
    ptime(d35p3,273).
    amplitude(d35p1,18.93).
```

2.3 Associations

Given representations of the geometry of the test situation and of the signals that result, we need some theory associating features of the signals and the geometry of the part under evaluation. It turns out that it is useful to make this association at several levels of abstraction, first mapping individual features of the signal to their interpretations, gradually working toward an interpretation of the entire signal.

The following theory covers ideal signals derived from the test blocks.

```
 normal(Block)  :-  signal(S,Block),peaks(S,2),
                    peak(S,1,P1),reflection(P1,front(Block)),
                    peak(S,2,P2),reflection(P2,back(Block)).
cracked(Block)  :-  signal(S,Block),peaks(S,3),
                    peak(S,1,P1),reflection(P1,front(Block)),
                    crack(C,Block),peak(S,2,P2),reflection(P2,C).
                    peak(S,3,P3),reflection(P3,back(Block)).
```

According to this theory, a block is normal if its NDE signal has two significant peaks; the first peak is a reflection from the front of the block and the second peak is a reflection from the back of the block. A block is cracked if the corresponding signal has three significant peaks; the first peak is a reflection from the front, but the second peak is a reflection from a crack in the block, and the third peak is the reflection from the back end.

A lower level of the theory associates individual features of the signal with their physical interpretations. There are two ways to do this. We illustrate them in terms of constraints on reflections from the front and back walls. The "shallow" approach is illustrated:

$$\begin{aligned}
\texttt{reflection(P,front(Block))} &:- \texttt{ptime(P,T),amplitude(P,A),} \\
&\quad\ \texttt{between(0,T,30),between(100,A,130).} \\
\texttt{reflection(P,back(block34))} &:- \texttt{ptime(P,T),amplitude(P,A),} \\
&\quad\ \texttt{between(240,T,250),between(10,A,30).}
\end{aligned}$$

The first statement says that a feature in a qualitative description of a NDE signal is a reflection from the front of a block if it occurs between times 0 and 30 and its amplitude is between 100 and 130. This statement is true of all the test blocks. The second statement says that a pulse is a reflection from the back wall of block34 if it occurs between times 240 and 250 and has an amplitude between 10 and 30. This statement is only true for block34.

This "shallow" approach associates observations directly with their interpretations. The weakness of this approach is that it leads to excessive numbers of ad hoc interpretation rules. For example, since the depths of the test blocks are all different, the reflections from the back walls will occur at different times, and the shallow approach requires separate rules for each block and time.

A relatively "deep" approach exploits underlying regularities to achieve a more compact theory. If we add general facts such as `feature(front(B),B)` and `feature(back(B),B)`, then the following theory of reflections covers all features of all the test blocks.

$$\begin{aligned}
\texttt{reflection(P,F)} &:- \texttt{peak(S,N,P),signal(S,B),feature(F,B),} \\
&\quad\ \texttt{depth_c(P,DP),depth_l(F,DF),requal(DP,DF).} \\
\texttt{requal(X,Y)} &:- \texttt{Diff is abs(X} - \texttt{Y),between(0,Diff,0.05).} \\
\texttt{between(X,Y,Z)} &:- \texttt{X} < \texttt{Y,Y} < \texttt{Z.} \\
\texttt{depth_c(P,D)} &:- \texttt{ptime(P,T),D is } 0.00499 * \texttt{T} - 0.0902.
\end{aligned}$$

The idea behind this theory is to tell the system the speed of ultrasound in aluminum so it can determine automatically whether a spike is a reflection from a feature at a given depth. A pulse P is a reflection of a feature F of block B if P is the Nth spike in the signal S derived from block B and the depth calculated from the peak is roughly equal to the depth of the feature.

In the case of known features, their depths are known and can be "looked up" using the predicate `depth_l`. The predicate `depth_c` is used to calculate depths from times.[4]

[4]Normally, Depth=Speed*Time. It turns out that the technicians collecting our data calibrated their instrument so that the time values were not measured in standard units. So the linear equation $Depth = 0.00499 \times Time - 0.0902$ encoded in the theory was derived using function finding techniques. See (O'Rorke, et al., 1991).

3 Abductive Interpretation of NDE Signals

Abduction is the construction and evaluation of explanations. In this section, we show how abduction can be used to classify parts by interpreting their corresponding NDE signals.

The abduction methods we use are based on logic programming. Our abduction engine (implemented in a PROLOG program called AMAL) essentially backward chains attempting to reduce observations to known facts by way of general laws. When it is impossible to prove the observation by grounding out in known facts, AMAL is capable of making assumptions along lines first proposed by Pople (Pople, 1973) and explored more recently in research such as (Ng & Mooney, 1991; O'Rorke, Morris & Schulenburg, 1990).

Figure 3 shows an explanation produced by AMAL. The explanation is a proof tree. The root of the tree is the conclusion of the diagnosis. Here, AMAL concludes that block34 is normal on the basis of its interpretation of NDE signal n34 taken from block34. The details of the interpretation support the conclusion. The indentation in the figure shows additional detail corresponding to lower levels of the proof tree.

The explanation is essentially as follows. The block is normal since the corresponding signal has two peaks. The first peak is interpreted as a reflection from the front of the block and the second peak is interpreted as a reflection from the back of the block. Most of the leaves of the tree (indented two levels in the figure) were given to AMAL as facts about the geometry of the block and the qualitative description of the signal. For example, the depth of the front wall is given as zero. But some leaves represent PROLOG computations at a hidden level of detail. For example, the predicates `requal` and `depth_c` are computed using PROLOG clauses but no trace is recorded in the explanation. In EBL terms, (DeJong & Mooney, 1986; Mitchell, Keller & Kedar-Cabelli, 1986), these predicates are considered to be "operational."

Figure 4 shows an interpretation of a signal from a cracked block. Note the underlined emboldened lines in the figure. These are hypotheses that AMAL has introduced in order to complete the explanation. They are not provable from the knowledge given initially.[5]

This interpretation identifies the first peak in the signal as the reflection from the front surface and the *third* peak as the reflection from the back surface. It hypothesizes the existence of a crack and assumes that the second peak is a reflection from this hypothetical defect. This assumption is made using "predicate-based abduction." An "assumability" predicate is used to automatically decide whether goals unprovable by unification with known facts or backward chaining are acceptable assumptions. This assumability predicate could be replaced with a query of the user. Alternatively, statistical information about the locations of cracks could be used to evaluate the likelihood that such assumptions are correct.

[5]unless closure assumptions are employed. See (Konolige, 1991).

```
normal(block34)
    signal(n34, block34)
    peaks(n34, 2)
    peak(n34, 1, n34p1)
    reflection(n34p1, front(block34))
        peak(n34, 1, n34p1)
        signal(n34, block34)
        feature(front(block34), block34)
        depth_c(n34p1, -0.022835)
        depth_l(front(block34), -0.02533)
        requal(-0.022835, -0.02533)
    peak(n34, 2, n34p2)
    reflection(n34p2, back(block34))
        peak(n34, 2, n34p2)
        signal(n34, block34)
        feature(back(block34), block34)
        depth_c(n34p2, 1.129855)
        depth_l(back(block34), 1.125)
        requal(1.129855, 1.125)
```

Figure 3: An Explanation Produced by AMAL

```
cracked(block33)
    signal(d33, block33)
    peaks(d33,3)
    peak(d33, 1, d33p1)
    reflection(d33p1, front(block33))
        peak(d33, 1, d33p1)
        signal(d33, block33)
        feature(front(block33), block33)
        depth_c(d33p1, -0.022835)
        depth_l(front(block33), -0.02533)
        requal(-0.022835, -0.02533)
    crack(_539,block33)
    peak(d33, 2, d33p2)
    reflection(d33p2,_539)
    peak(d33, 3, d33p3)
    reflection(d33p3, back(block33))
        peak(d33, 3, d33p3)
        signal(d33, block33)
        feature(back(block33), block33)
        depth_c(d33p3, 1.00261)
        depth_l(back(block33), 1)
        requal(1.00261, 1)
```

Figure 4: An Explanation Involving a Hypothetical Defect

4 Advantages

A strength of the method advocated here is that it is can handle situations that would be difficult or impossible without abduction. The signal shown earlier was a nearly ideal signal. Typically, one must interpret more complex signals containing noise that survives the mapping from raw time series data to a qualitative description of the signal.

Consider the following qualitative signal description.

```
signal(d33,block33).
peaks(d33,4).
  peak(d33,1,d33p1).
    ptime(d33p1,13.5).
    amplitude(d33p1,115.26).
  peak(d33,2,d33p2).
    ptime(d33p2,71.5).
    amplitude(d33p2,19.71).
  peak(d33,3,d33p3).
    ptime(d33p3,219).
    amplitude(d33p3,14.29).
  peak(d33,4,d33p4).
    ptime(d33p4,426.5).
    amplitude(d33p4,6.65).
```

The fourth peak is noise that survives the mapping to a qualitative description. This signal is easily explained: the anomolous fourth pulse is an echo of the original reflection from the back wall. Our approach handles this difficulty if we add the following statements about echoes to the theory of signal propagation.

```
    cracked(Block)  :-  signal(S,Block),peaks(S,4),
                        peak(S,1,P1),reflection(P1,front(Block)),
                        crack(C,Block),peak(S,2,P2),reflection(P2,C).
                        peak(S,3,P3),reflection(P3,back(Block)).
                        peak(S,4,P4),echo(P4,back(Block)).
echo(P,back(Block)) :-  depth_c(P,DP),depth_l(back(Block),DB),requal(DP,2*DB).
```

The idea behind this extension of the idealized theory is that, while much of an initial reflection from the back wall is absorbed by the transducer, some energy may reflect off the front wall and again off the back wall. The echo of the initial reflection will arrive twice as late as the initial reflection. (It is as if the echo comes from a "phantom" back wall twice as deep as the depth of the block.) The theory of echoes above is based on simple physics of signal propagation. It is general in the sense that it works for any of the nine blocks. It should be trivial to extend this theory to cover an arbitrary number of echoes.

5 Related Work, Limitations, and Future Work

Our work is closely related to earlier studies of signal interpretation in medical domains. The most important relevant work is the KARDIO study (Bratko, Mozetiĉ & Lavraĉ, 1989). It involved the development of a theory relating faults in a model of the electrical system of the heart to qualitative descriptions of ECG waveforms.

One limitation of the work described here is that only one spatial dimension (depth) is taken into account. This is sufficient for many diagnostic situations (e.g., pulse-echo "A-scans"), but not for others (e.g., "C-scans"). See (Gallagher, Giessler, Berens & Engle, 1984; McMaster, 1959). Additional dimensions could be used to help produce additional explanations. Adding width information, for example, could be useful even in interpreting "A-scans." Note that the width of the transducer (and of the ultrasonic pulse) is larger than the width of the simulated defect in the test block shown in Figure 1. This accounts for the fact that the A-scan data shown in Figure 2 shows a reflection from the back wall in addition to the reflection from the simulated crack. (Normally, cracks are wider than pulses, so the pulses are completely reflected by the cracks and there is no reflection from the back wall.) A two-dimensional NDE theory could be used to compute the widths of small cracks from the known width of the pulse and the amplitude of the reflections from cracks and back walls.

Another limitation that we are interested in addressing is the possibility of ambiguous interpretations. Some signals can give rise to several explanations. We would like to have some way of evaluating competing interpretations. Work on theories of explanatory coherence (Thagard, 1989) and on methods for finding most probable explanations seems relevant. Techniques for incorporating probabilities could be useful in NDE since cracks tend to occur more frequently in known locations and orientations due to stress patterns in the materials of interest.

In addition, we would like to explore the use of hypothetico-deductive reasoning to suggest additional measurements that could resolve ambiguous NDE readings. In scanning parts that have regularly spaced holes indistinguishable from cracks, it would be useful if the NDE program suggested taking another measurement a fixed distance away to distinguish between the two possible interpretations of an identical signal. Hypothetico-deductive reasoning also would be useful in suggesting alternative testing scenarios. For example, a spacer helps discriminate hypothetical cracks near the surface from noise due to "near-field effects." Wedges are sometimes used to determine whether a weak spike in the signal actually corresponds to large cracks at an oblique angle. Or a C-scan might be called for in order better to interpret results of an initial A-scan.

Acknowledgments

This research is part of a larger collaborative research project involving the University of California, Irvine, Douglas Aircraft Company, the University of Missouri-Rolla, Graduate Engineering Center, and McDonnell Douglas Research Laboratories. Earlier results of this research were reported in (Amirfathi, et al., 1991; O'Rorke, et al., 1991; St. Clair, et al., 1990). The authors gratefully acknowledge M. R. Collingwood and D. J. Hagemaier of Douglas Aircraft Company for providing NDE domain knowledge and test data. Thanks also to John Gross and Michael Amirfathi of the Douglas Aircraft AI Group for supporting and for actively participating in this research. Thanks to Deepak Kulkarni at NASA Ames for informing us about methods for mapping signals into qualitative descriptions, and to Kiriakos Kutulakos at the Univ. of Wisconsin, Madison, for scale-space code he developed at NASA Ames. Discussions with Igor Mozetiĉ on the KARDIO methodology helped provide the initial impetus for this line of research.

References

Amirfathi, M. M., Morris, S., O'Rorke, P., Bond, W. E., & St. Clair, D. C. (1991). Pattern recognition for nondestructive evaluation. In L. Mallette (Ed.), *Proceedings of the 1991 IEEE Aerospace Applications Conference.* Crested Butte, CO: IEEE Computer Society Press.

Bratko, I., Mozetiĉ, I., & Lavraĉ, N. (1989). *KARDIO: a study in deep and qualitative knowledge for expert systems.* Cambridge, MA: The MIT Press.

DeJong, G. F., & Mooney, R. (1986). Explanation-based learning: An alternative view. *Machine Learning*, *1*(2), 145-176.

Gallagher, J. P., Giessler, F. J., Berens, A. P., & Engle, R. M. (1984). *USAF Damage Tolerant Design Handbook: Guidelines for the Analysis and Design of Damage Tolerant Aircraft Structures* (Technical Report Air Force Report No. AFWAL-TR-82-3073). Wright-Patterson Air Force Base.

Konolige, K. (1991). *Abduction vs. closure in causal theories* (Technical Report 505). SRI International.

McMaster, R. C. (1959). Ultrasonic Test Principles, Section 43. *Nondestructive Testing Handbook*

Mitchell, T. M., Keller, R. M., & Kedar-Cabelli, S. T. (1986). Explanation-based generalization: A unifying view. *Machine Learning*, *1*(1), 47–80.

Ng, H. T., & Mooney, R. J. (1991). An efficient first-order Horn-clause abduction system based on the ATMS. *Proceedings of the Ninth National Conference on Artificial Intelligence* (pp. 494–499). Anaheim: MIT Press/AAAI Press.

O'Rorke, P., Morris, S., Amirfathi, M. M., Bond, W. E., & St. Clair, D. C. (1991). Machine learning for nondestructive evaluation. In L. A. Birnbaum, & G. C. Collins (Ed.), *The Eighth International Workshop on Machine Learning* (pp. 620–624). Evanston, IL: Morgan Kaufmann.

O'Rorke, P., Morris, S., & Schulenburg, D. (1990). Theory formation by abduction: A case study based on the chemical revolution. In J. Shrager, & P. Langley (Eds.), *Computational models of scientific discovery and theory formation* (pp. 197–224). San Mateo, CA: Morgan Kaufmann.

Partridge, D. (1987). The scope and limitations of first generation expert systems. *Future Generation Computer Systems*, *3*(1), 1-10.

Pople, H. E. (1973). On the mechanization of abductive logic. *Proceedings of the Third International Joint Conference on Artificial Intelligence* (pp. 147–152). Stanford, CA: Morgan Kaufmann.

St. Clair, D. C., Bond, W. E., & Sabharwal, C. L. (1990). Measuring concept strength in classification trees. *Proceedings of the Fifth International Symposium on Methodologies for Intelligent Systems.* .

Thagard, P. (1989). Explanatory coherence. *The Behavioral and Brain Sciences*, *12*(3), 435–502.