INVARIANCE ALGORITHMS FOR NONDESTRUCTIVE EVALUATION

Shreekanth A. Mandayam

Department of Electrical & Computer Engineering
Rowan University
201 Mullica Hill Road, Glassboro, NJ 08028

ABSTRACT

A new class of invariant pattern recognition algorithms is required for interpreting nondestructive evaluation signals that occur during in-line inspection of components with varying material properties. This paper presents the theoretical development of these invariance algorithms and provides experimental validation of these algorithms using applications in magnetic flux leakage NDE and ultrasound NDE.

1. INTRODUCTION

Invariant pattern recognition algorithms form the heart of most visual/image recognition techniques. The field of invariants is not new; many algorithms, rooted in rigorous mathematical theory, have been developed over the years. However, developments in invariant theory for images have focused on "classical" parametric variations such coordinate transformations such as translation, rotation and scaling. The development of general mathematical techniques that provide invariant features for operational transformations is still largely unexplored.

Operational parametric variations occur as the result of changing physical conditions during an imaging process – as in the interpretation of nondestructive evaluation (NDE) signals obtained during the interrogation of infrastructure composed of varying material properties. Local variations in the material properties cause the received NDE signals to exhibit uncontrolled, and often unpredictable variations making signal inversion inaccurate and unreliable. Classical invariant pattern recognition/signal processing techniques cannot model such parametric variations; a new class of invariance transformation algorithms is called for to render signals invariant to operational conditions that include variations in material properties. This paper presents the theoretical development of this new class of invariant signal processing algorithms and provides experimental validation of these algorithms using applications in magnetic flux leakage NDE and ultrasound NDE.

This paper is organized as follows. Following this introduction, the research objectives are presented and the proposed invariance algorithm is described. The next section presents application examples demonstrating the validity and robustness of the invariance transformation algorithm. Two applications are presented – thickness-invariant characterization of metal pipeline segments using magnetic flux leakage interrogation and composition-invariant characterization of concrete pipe segments using ultrasonic testing. The paper concludes with a discussion on the general nature of the invariance transformation algorithms that have been developed, and their potential application to a diverse class of problems.

2. INVARIANCE TRANSFORMATIONS

The objective of the invariance transformation is to isolate information relating to the object geometry irrespective of the operational parameters associated with the imaging or interrogation process. The algorithm should not only compensate for these variables, but also ideally, be able to operate without a precise knowledge of these variables. Such algorithms are, in fact, a part of many biological systems. For example, the human visual system is able to estimate the size of an object, regardless of its distance from the observer (obviously within a certain range of distances). The visual system accomplishes this by making two measurements, one with each eye. These two measurements are dissimilar and this dissimilarity is exploited in the visual cortex for synthesizing the composite 3-D view of the object, along with fairly accurate estimates of its size. The key process that allows for distance-invariant object size estimation is the fact that the image seen by each eye differs slightly from the other. This procedure can be modeled mathematically, and a generalization of the mathematical procedure can be developed for performing parameter-invariant image characterization. Two dissimilar "views" of the test specimen can be obtained by utilizing the two inspection modalities. The invariance transformation is an algorithm that can combine disparate signals by selectively promoting desired parametric variations (e.g. object geometry related changes) and suppressing unwanted ones (operational procedure related changes).

A transformation that combines disparate signals can be designed when the signal interpretation problem is recast as a problem in the interpolation of scattered multidimensional data. The field of computational mathematics is rich with sophisticated techniques for data interpolation. Of all these techniques, feed-forward neural networks have triumphed as the ones possessing the widest range of application. These include multiquadric surface interpolation, as in a radial basis function (RBF) networks [1] fuzzy inference systems (FIS) [2] and wavelet transform based networks (WaveNets) [3]. The key requirement for designing an invariance transformation procedure is a set (consisting of at least two) signals that originate from the same process.

Given two signals, X_A and X_B, characterizing the same phenomenon, two distinct initial features, $x_A(d, l, t)$ and $x_B(d, l, t)$, are chosen, where t represents an operational variable (for instance, material property of the object under test) and d and l represent geometrical parameters (for instance, defect depth and length, respectively). x_A and x_B are chosen such that they have dissimilar variations with t. A systematic procedure is developed to obtain a feature, h, which is a function of x_A and x_B and invariant to the parameter, t. For simplicity, x_A and x_B are considered to be dependent on only three parameters d, l and t. We need to find a function, f, such that

$$f\{ x_A (d, l, t), x_B (d, l, t)\} = h(d,l) \qquad (1)$$

Given two functions g_1 and g_2,a sufficient condition to obtain a signal invariant to t can be derived as

$$h(d,l)\ ?\ \ g_1 (x_A) = g_2 (x_B) \qquad (2)$$

where ? refers to a homomorphic operator. Then the desired t-invariant response is defined as

$$f(x_A, x_B) = g_2 (x_B)\ ?\ \ g_1^{-1}(x_A) = h(d,l) \qquad (3)$$

To implement this procedure, the functions h, g_1 and g_2 need to be obtained. Since h is a user-defined function, it can be chosen conveniently; for example, a linear combination of d and l. The function g_2 could be used to serve as a "conditioning" function, chosen to better condition the data. For example, if x_B contains widely spread values, g_2 can be chosen to be a logarithmic function. Having chosen h and g_2 arbitrarily, a suitable functional form is assumed for g_1, whose coefficients are to be determined. This is done by solving a set of simultaneous equations at discrete points, (d_i, l_j, t_k); i: 1 to m; j: 1 to n; k: 1 to p, in the data space. That is,

$$h(d_i, l_j)\ ?\ \ g_1\{ x_A (d_i, l_j, t_k)\} = g_2\{ x_B (d_i, l_j, t_k)\} \qquad (4)$$

should be solved exhaustively. This is nothing but a problem in multidimensional interpolation. Invariance is possible using this method only if a unique solution to (4) exists, which depends on an appropriate choice of g_1. Designing an invariance transformation function in essence translates to finding the most suitable g_1 for the data set given. As mentioned earlier, functions modeled by feedforward neural networks are ideal functional forms for g_1. In a practical application, images from two different inspection modalities (transducer frequency, transducer orientation, etc.) could be the two dissimilar signals that are required by this invariance transformation technique.

3. APPLICATION EXAMPLES

The invariance transformation algorithm described in the previous section is applied for interpreting NDE signals obtained from two kinds of inspection processes – metal gas pipelines that are inspected using magnetic flux leakage methods and concrete water pipelines that are inspected using ultrasonic techniques. Laboratory experiments have been developed for generating a suite of NDE signals for both kinds of inspection methods – these have been used to exercise the invariance algorithms. Details of the experimental process and typical application results are presented in the following subsections.

3.1. Magnetic flux leakage inspection

Magnetic flux leakage (MFL) inspection is the method of choice for inspecting a large portion of the 280,000-mile natural gas transmission pipeline system [4]. These pipes, usually buried underground, are 24 – 36 inches in diameter and are constructed from X-Grade steel. Along any length of the pipe, pipe thickness and magnetic characteristics vary – these lead to changes in the magnetic flux leakage image of the pipe segment, thus making defect characterization difficult. Invariance transformation algorithms can potentially render the magnetic images invariant to the effects of pipe-wall thickness and/or magnetization characteristic, while at the same time, preserve image variations that occur due to defect depth. Different components of the magnetic flux density vector can be used to generate the disparate inspection signals – a set of orthogonal sensors can be employed to record the various components.

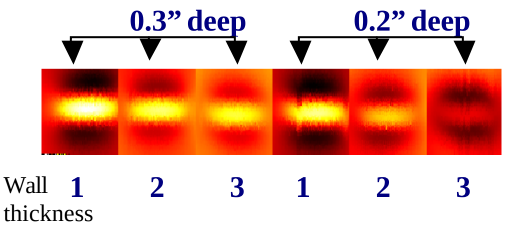


Fig. 1. Magnetic flux leakage images from pipes with varying wall thickness and defect depth.

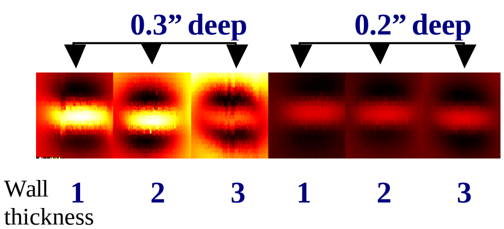


Fig. 2 Magnetic flux leakage images after invariance transformation.

Figure 1 shows magnetic images from sections of pipe-walls with 3 different wall-thicknesses and 2 different defect depths. Figure 2 shows the corresponding magnetic images after they have been processed with the invariance transformation algorithm described in the previous section. The results demonstrate that gray level variations due to changing magnetization level that occur due to changing pipe-wall thicknesses are reduced/eliminated whereas gray level variations due to defect geometry are preserved.

3.2. Ultrasonic inspection

Ultrasonic inspection is widely used for assuring the integrity of a variety of metallic and non-metallic objects, including composites [5]. In this paper, we focus on using ultrasonic NDE for inspecting concrete specimens representative of wastewater pipelines [6]. An immersion ultrasound system with pairs of transducers are used to perform through-transmission inspection of defective concrete samples. The composition of the concrete is varied from a cement + sand mix to a cement + sand + aggregate mixture; the defect depth is also varied. The inspection is conducted at two frequencies – 500 kHz and 1 MHz; the two sets of C-scan images are used to generate peak-to-peak signal amplitudes related to defect depth. These form the disparate signals required for the invariance transformation, which can be applied to provide a peak-to-peak signal amplitude that is invariant to the concrete

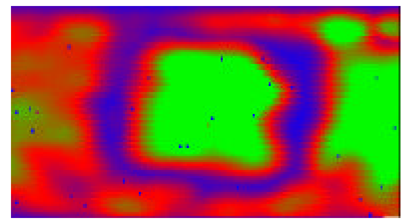


Fig. 3. Ultrasound C-scan image obtained by scanning a 6”x4”x2” concrete (cement + sand + water mixture) specimen containing a 1”x1”x0.5” rectangular slot-shape defect using a pair of 500 kHz ultrasound transducers.

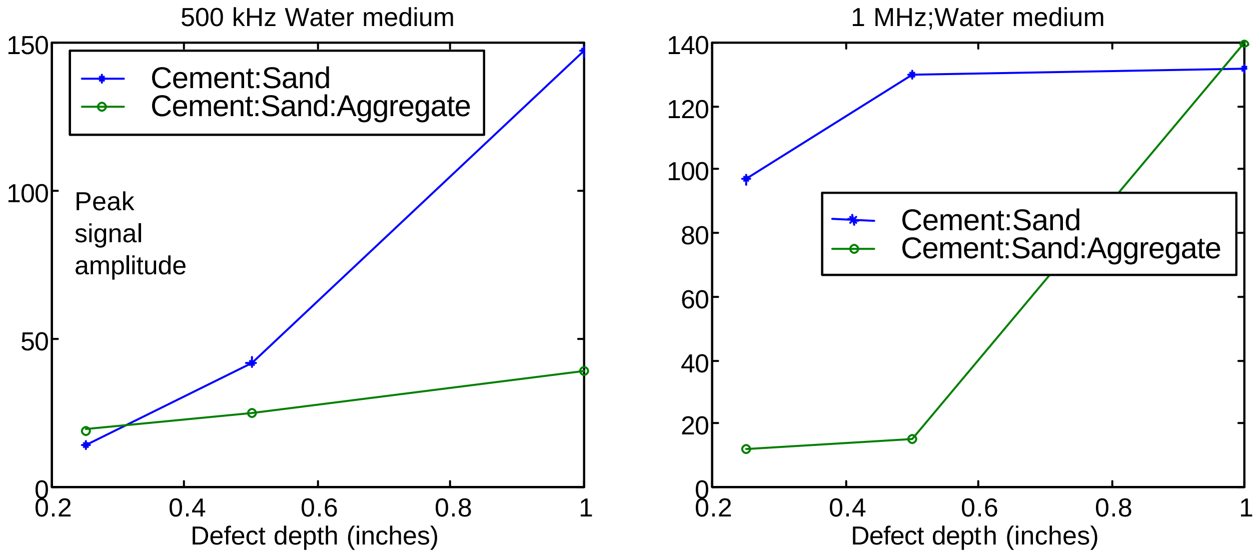
composition and yet responds to changes in defect depth. Figure 3 shows a sample C-scan obtained from a concrete specimen embedded with a rectangular defect. Peak-to-peak signal amplitudes at two different transducer frequencies inspecting concrete specimens with varying composition and defect depth can be seen in Figures 4 (a) and (b). Figure 5 shows the results of the invariance transformation. This demonstrates a particularly useful application of invariance transformations to NDE – concrete, by its heterogeneous nature is extraordinarily difficult to characterize.

4. CONCLUSIONS

The results presented in this paper demonstrate the validity of using invariance transformation algorithms for two very different NDE techniques – the magnetic flux leakage inspection method, which is a static (dc) process and the ultrasonic inspection method, which is a high frequency process. The algorithm is sufficiently general in that it can be used for invariant pattern recognition in many imaging applications far removed from NDE. The technique is robust and easy to implement – all that is required is a suite of specimen signatures for designing the invariance transformation. In the NDE area, such transformations are a necessary pre-processing stage for developing advanced inspection and evaluation techniques.

5. REFERENCES

[1] Michelli, C. A. , “Interpolation of scattered data: distance matrices and conditionally positive definite functions,” *Constructive Approximation*, Vol. 2, pp. 11-22, 1986.



(a) (b)

Fig. 5. Peak-peak signal amplitudes from C-scans of 6”x4”x2” concrete specimens made with two different compositions scanned at two different frequencies – 500 kHz and 1 MHz. Specimens contain rectangular slot-shaped defects of varying depths – 0.25”, 0.5” and 1”.

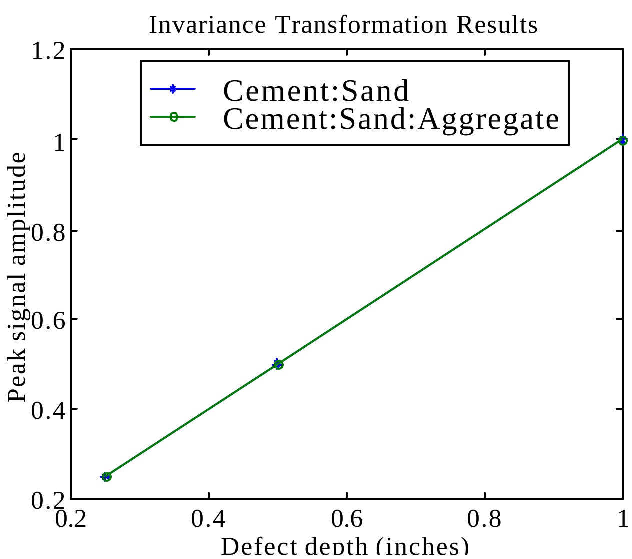


Fig. 6. Invariance transformation results for the concrete specimen scans.

[2] Sudkamp, T. and Hammell, R. J., II, “Interpolation, completion and learning fuzzy rules,” *IEEE Transactions on Systems, Man and Cybernetics*, Vol. 24, No. 2, pp. 332-342, 1994.

[3] Bakshi, B. R. and Stephanopoulos, G., “Wave-net: A multiresolution, hierarchical, neural network with localized learning,” *AIChE Journal*, Vol. 39, pp. 57-81, 1993.

[4] Udpa, L., Mandayam, S., Udpa, S., Sun, Y., and Lord, w., “Developments in gas pipeline inspection technology,” Materials Evaluation, Vol. 54, No. 4, pp. 467-472, April 1996.

[5] Krautkramer, J., and Krautkramer, H., *Ultrasonic Testing of Materials*, 3rd Ed., Springer-Verlag, Berlin, 1983.

[6] Mandayam, S., Jahan, K. and Cleary D.B., “Ultrasound inspection of wastewater concrete pipelines – signal processing and defect characterization,” to appear in *Review of Progress in Quantitative NDE*, API, 2000.