A MULTIRESOLUTION APPROACH FOR CHARACTERIZING MFL SIGNATURES FROM GAS PIPELINE INSPECTIONS

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INTRODUCTION

Gas transmission pipelines are routinely inspected using a magnetizer-sensor assemblage, called a pig, which employs magnetic flux leakage (MFL) principles to generate defect signals that can be used for characterizing defects in the pipeline[1]. Previously reported work[2] demonstrated that radial basis function(RBF) networks[3-5] can be employed to characterize MFL signals in terms of defect geometry. Further development of this research work, related to three dimensional defect characterization are reported elsewhere in these proceedings. This paper presents an alternate neural network approach based on wavelet functions to predict three dimensional defect profiles from MFL indications. Wavelet basis function neural networks are comprised of a hierarchical architecture and are capable of multiresolution functional approximation. They offer a powerful alternative to RBF based signal-defect mapping techniques, in that the level of output prediction accuracy can be controlled by the number of resolutions in the network architecture. Consequently, the network itself can be employed to generate measures of confidence for its prediction. Such confidence factors may prove to be extremely useful in pipeline inspection procedures since they can form a basis for subsequent remedial measures. The feasibility of employing a wavelet basis function network for characterizing defects in pipelines is demonstrated by predicting defect profiles from experimental magnetic flux leakage signals.

DEFECT CHARACTERIZATION PARADIGM

Artificial neural networks(ANNs) have been used extensively for solving inverse problems in nondestructive evaluation(NDE). The inverse problem is recast as a problem in multidimensional interpolation, which consists of finding the unknown nonlinear relationship between inputs, x and outputs, F, in a space spanned by the activation functions associated with the neural network nodes. The input space, x, corresponds to the NDE signal generated by a pig and the output corresponds to the

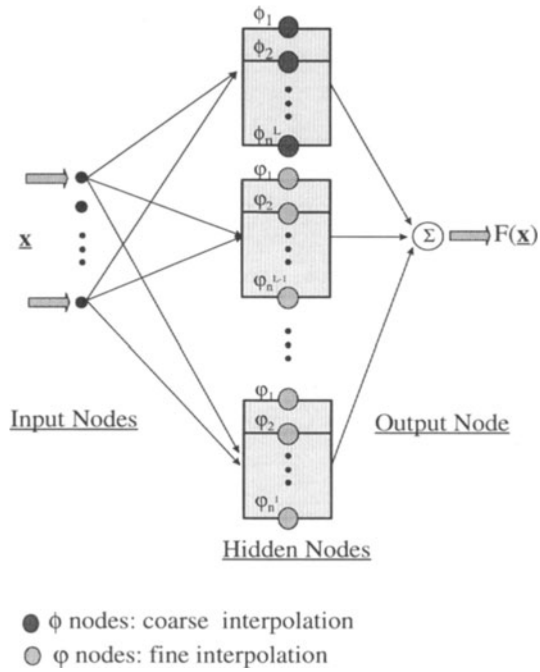


Figure 1: Architecture of a wavelet network.

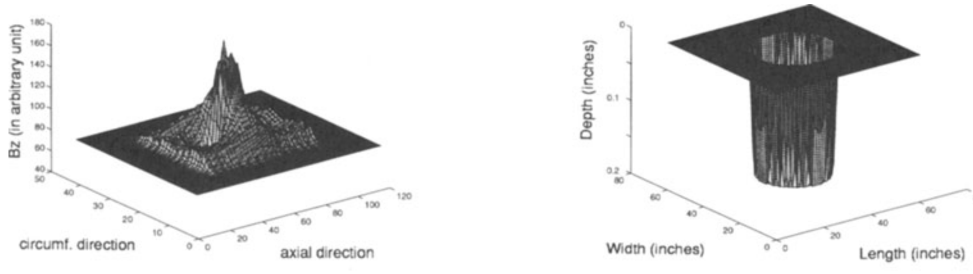
defect characteristics such as length, width, depth and profile. Prior work has shown that RBF type neural networks[6] can be employed for characterizing defects. In situations where defect related features occur at multiple resolutions in the NDE signal, single functional mapping schemes are not necessarily optimal. This calls for the use of multiresolution functional approximation techniques such as those as using wavelet basis functions. A brief introduction to wavelet basis function(WBF) neural networks follows.

WAVELET BASIS FUNCTION NEURAL NETWORKS

Bakshi and Stephanopoulos[7] introduced Wavelet Networks whose basis functions are drawn from a family of orthogonal wavelets. Wavelet networks are similar to RBF ANNs. Both networks have a single hidden layer. In contrast to the RBF, a wavelet network has sets of nodes depending on the number of resolutions. The two types of nodes are called the scaling function nodes, and the wavelet function nodes. The architecture of a typical wavelet network is shown in Fig. 1.

Wavelet networks are developed based on the following principles. By using multiresolution decomposition[8], a signal, f, can be represented by

$$\begin{aligned} f &= \textstyle\sum_j < f, \phi_j^n > \phi_j^n \\ &= \textstyle\sum_j < f, \phi_j^{n-1} > \phi_j^{n-1} + \sum_j < f, \psi_j^{n-1} > \psi_j^{n-1} \\ &= \textstyle\sum_j < f, \phi_j^l > \phi_j^l + \sum_{k=l}^{n-1} \sum_j < f, \psi_j^k > \psi_j^k \end{aligned}$$



(a) Input MFL signal (b) Desired profile

Figure 2: Mapping from an MFL signature to a defect profile.

$$= \sum_j s_j^l \phi_j^l + \sum_{k=l}^{n-1} \sum_j d_j^k \psi_j^k \tag{1}$$

where $<,>$ represents the inner product, ϕ is known as the scaling function, ψ is the wavelet function and j and k represent the translation and dilation parameters respectively. From equation (1), the unknown function F can be approximated using a limited number of multiresolution basis functions.

$$F = \sum_{j=1}^{N_L} s_j^L \phi_j^L + \sum_{k=1}^{L} \sum_{j=1}^{N_k} d_j^k \psi_j^k \tag{2}$$

where L is the number of resolutions, and N_k is the number of dilations at each resolution. The wavelets ψ_j^k are generated through translation and dilation of the mother wavelet, given by $\psi_j^k(x) = 2^{k/2}\psi\left(2^k x - j\right)$.

For function approximation problems, Gaussian functions are chosen typically as the basis functions, since they possess good approximation properties. In order to satisfy the wavelet basis admissibility conditions, the scaling function consists of a Gaussian and the wavelet function is composed of its first derivative. The function approximation equation (2) can be written as

$$F = \sum_{j=1}^{N_L} s_j^L \phi_j^L \left(\|\bar{x} - \bar{c}_j\|\right) + \sum_{k=1}^{L} \sum_{j=1}^{N_k} d_j^k \psi_j^k \left(\|\bar{x} - \bar{c}_j\|\right) \tag{3}$$

where the s's and d's are the coefficients and c_i the centers of the basis functions and the scaling and wavelet functions are respectively:

$$\begin{aligned} \phi &= \exp\left[\frac{\|\bar{x}-\bar{c}_j\|^2}{2\sigma^2}\right] \\ \psi &= \frac{\|\bar{x}-\bar{c}_j\|}{\sigma^2} \exp\left[\frac{\|\bar{x}-\bar{c}_j\|^2}{2\sigma^2}\right] \end{aligned}$$

In this application, x corresponds to the defect signature generated by the sensors in the inspection tool. and F represents the corresponding three dimensional defect profile. The mapping is illustrated in Fig. 2.

NETWORK TRAINING

Network training essentially consists of determining (a) the basis function centers (b) the support of the basis functions and (c) the network weights. The basis function

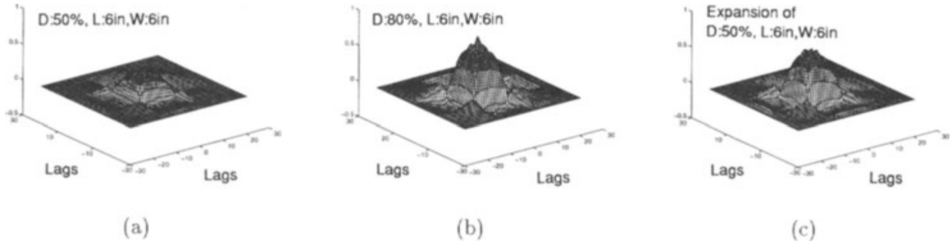


Figure 3: Illustration of the dyadic expansion (a) A typical covariance matrix of 50% depth MFL signal. (b) A typical covariance matrix of 80% depth MFL signal. (c) Expansion of the covariance matrix (a).

centers are obtained typically by means of a K-means clustering algorithm or one of its several variants. Previous studies have shown that the performance of the network is highly dependent on the location and number of centers. Conventional methods to determine the optimal location and support of the centers are computationally intensive[2]. To overcome this disadvantage, this paper proposes a dyadic expansion scheme to select the location of the centers which is based on the following principle. The covariance matrices of MFL signals associated with defects which have the same width and length, are similar. This feature is exploited to construct a dyadic expansion scheme.

The dyadic expansion scheme consists of the following steps:

1. Obtain the covariance matrix, C

2. Calculate eigenvalue matrix(V) and eigenvector matrix(D) of C given by

$$C \cdot V = V \cdot D \tag{4}$$

where $D = diag\{\lambda_1, \lambda_2, \cdots, \lambda_n\}$, $V = \{v_1, v_2, \cdots, v_n\}$ and v_i are the column vectors of V.

3. C is then decomposed as follows

$$\begin{aligned} C &= V \cdot D \cdot V^{-1} \\ &= \textstyle\sum_{i=1}^{n} \lambda_i \cdot v_i \cdot v_i^{\mathrm{T}} \\ &= \textstyle\sum_{i=1}^{n} \lambda_i \cdot P_i \end{aligned} \tag{5}$$

where P_i is a projection onto a eigenspace for λ_i.

4. A expanded covariance matrix can be obtained by the equation

$$C_k = 2^k(\lambda_1 \cdot P_1 + \cdots + \lambda_n \cdot P_n) \tag{6}$$

Fig. 3 illustrates the dyadic expansion of the MFL signal obtained from a 50% depth defect.

This scheme is combined with K-means algorithm to calculate the location of all the centers. The complete network training procedure is summarized in Fig. 4. A

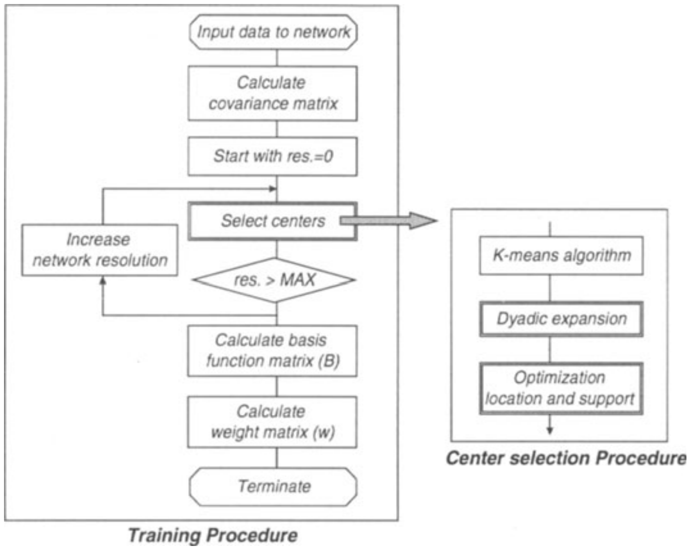


Figure 4: Training procedure.

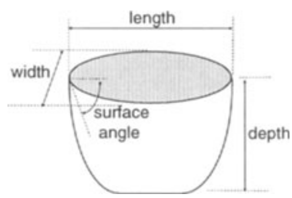


Figure 5: Geometry of defect profile.

hybrid learning method which includes a gradient descent procedure as a supervised method, is used to adjust the location and support of centers. Gradient values at the coarsest resolution are calculated as follows

$$\begin{aligned} \nabla_{c_j} &= -\sum_i (d_i - y_i) w_j \phi_{ij} (x_i - c_j) \frac{1}{\sigma_j^2} \\ \nabla_{\sigma_j} &= -\sum_i (d_i - y_i) w_j \phi_{ij} \|x_i - c_j\|^2 \frac{1}{\sigma_j^3} \end{aligned} \tag{7}$$

where d is the desired network output value, y is the predicted value, w is the weight coefficient and σ is the support of the basis function.

RESULTS

The wavelet basis function network was employed for characterizing defects in gas pipelines. A section of pipe was machined with cup cake shape defects, shown in Fig. 5. The input data to the network consists of covariance matrices of MFL signatures that were captured by an experimental test facility. The desired output is

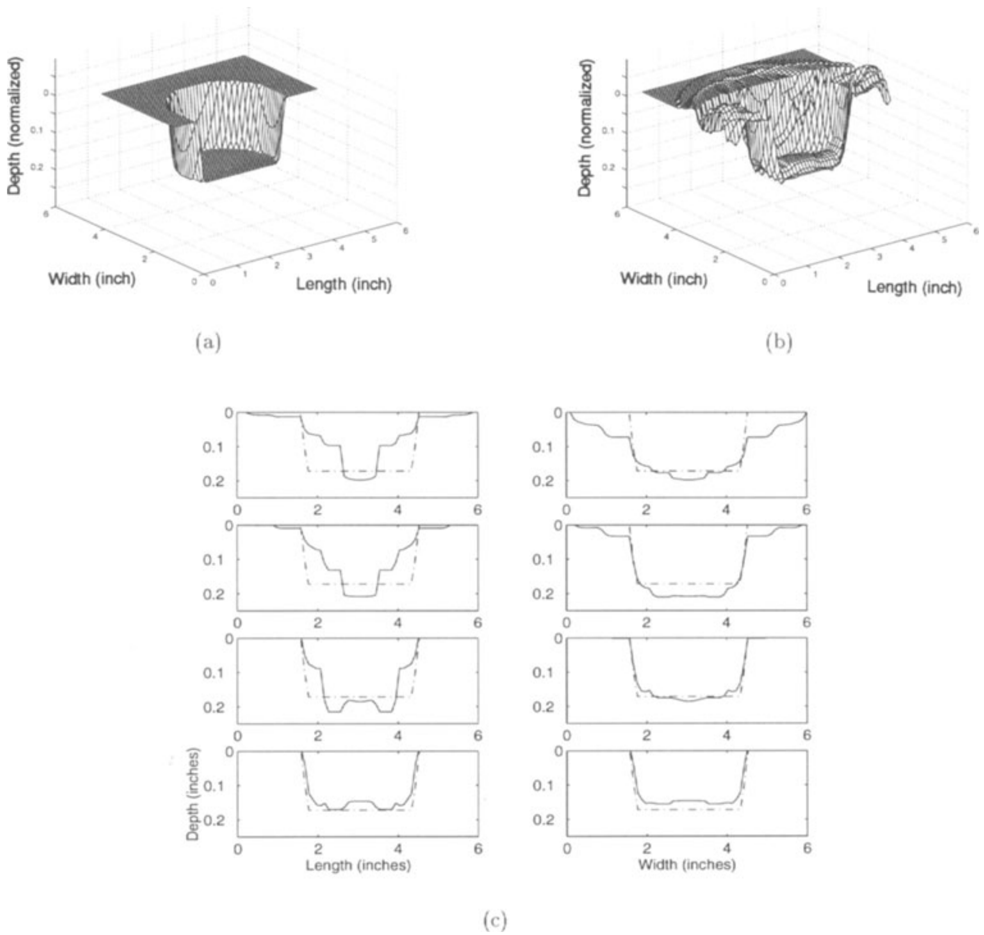


Figure 6: Comparison of true and predicted defect profiles (depth:50%,length:3in,width:3in). (a) True defect profile. (b) Predicted defect profile. (c) Effect of changing the number of resolutions (true profile: -·-, predicted profile: —).

a matrix that indicates the degree of metal loss in the pipe wall and corresponds to the defect profile.

The network was trained using 41 data sets, generated by defects which differed in depth(50%,80%), width(1,2,3,4.5,6 inches), length(1,2,3,4.5,6 inches) and surface angle($23°, 45°, 90°$).

Subsequently, the network was used to predict the profile of a defect whose signal was not contained in the training data. Fig. 6 displays the true defect profile(a), its predicted profile(b) and line scans along the width and length with changing number of network resolutions(c). Results indicate that the profile predicted in the case of a 3"(l) x 3"(w) defect is very close to the true profile. Also, results obtained by using a network of multiple resolutions, showed that the level of output accuracy could be increased in a controlled manner by increasing the number of resolutions.

CONCLUSIONS

The results of this study demonstrate that wavelet basis function neural networks with dyadically expanded centers can successfully map MFL signatures to 3 dimensional defect profiles. Furthermore, the accuracy of the output can be controlled by systematically varying the number of network resolutions. However, in order to obtain accurate defect profile predictions, a consistent and comprehensive set of training data is necessary.

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