Classification of Eddy Current NDT Data
by Probabilistic Neural Networks

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Abstract

In this paper we discuss the use of the Probabilistic Neural Network (PNN) for the classification of the defects detected via the Remote Field Eddy Current (RFEC) inspection technique. The neural network is employed in order to associate each defect to one of the predefined classes. Each defect is represented by means of the phase response of the probe system. The reported results show that the proposed artificial neural network allows reliable classification results.

1. Introduction

Defect classification in steel-industry plants is a crucial phase in the manufacturing process. Surface defects are indeed important quality metrics for customers and determine the quality of the product. Usually, surface defects are organized by families (sets of defects of the same nature); consequently, the classification must give as result the family that the defect belongs to. Until few years ago, current approach relied on human inspectors specially trained for the job, but the inspection could not be completely reliable and was subject to important performances variability. Better information on defects may provide valuable direct feedback for process control to reduce costs of quality and to increase manufacturing productivity. The Neural Network based approach gives a cost/time efficient solution to classification problems; when the available data amount is limited and time to classify is constrained by the manufacturing process, especially Probabilistic Neural Networks seem to represent an excellent and reliable approach [2].

In this paper we present surface defects identification by the Rotated Kernel Probabilistic Neural Network (RKPNN) introduced by Galleske and Castellanos in [4]. After giving a brief description of the problem at hand and of the RKPNN-based solution proposed here, we present experimental results obtained by running our RKPNN code on measured eddy-current inspection data in order to illustrate the effectiveness of the proposed approach. The results confirm that it is possible to obtain 100% correct classification on the set of untrained patterns by properly tuning the free parameter of the network.

2. Remote Field Eddy Current (RFEC) Inspection

The RFEC is an eddy current pipe inspection technique [1]. A probe, that consists of an exciter coil and one or more detectors at an axial distance over two diameters from the exciter, is pulled through a conductive pipe. The exciter coil is driven with relatively low frequency sinusoidal current producing a magnetic field. The exciter field induces strong eddy currents in the inner walls of the pipe near the exciter. These currents produce their own magnetic fields, which are always in opposition to the exciter field. Because eddy currents experience conductive losses in the pipe walls, these counter fields do not fully balance the exciting field. Anomalies are thus detectable because they interfere with the preferred eddy current paths and magnetic fields. At a distance of about two pipe diameters or more from the exciter, a field (termed the remote field) can be detected: it is sensitive to anomalies or perturbations in the pipe walls in the path of the interrogating magnetic field, such as metal loss, cracks, corrosion or wall thinning.

3. Density Estimation and Classification by the Probabilistic Neural Networks

The Probabilistic Neural Network (PNN) by Specht [3,4,5] is a network formulation of probability density estimation. PNN has proven to be more time efficient than conventional back-propagation based networks and has been recognized as an alternative in real-time classification problems. In order to classify a feature pattern-vector \( x \in \mathbb{R}^M \), that is to assign the pattern to one among \( K \) predefined classes, the conditional density \( P(x|C_k) \) of each class \( C_k \) is estimated since it represents the uncertainty associated to class attribution; then these estimates are combined by the rule of Bayes to yield a-posteriori class probabilities \( P(C_k|x) \) that allow to make optimal decisions [3,4,5]. In the PNN, conditional density estimation is accomplished by implementing the Parzen window technique. One possible way of looking at this technique is to build a sphere of influence \( p(s,x) \) around each training (known) sample \( s \) and to add them up for each of the \( K \) classes:

\[
P(x|C_k) = \sum_{s \in C_k} p(s,x) .
\]
In original Specht’s implementation, the basis functions used as windows are the Gaussian kernels:

\[ p(s,x) = \exp\left(-\frac{||x-s||^2}{2\sigma^2}\right), \quad (3) \]

where the only free parameter is the width \( \sigma \) of the Gaussians.

The neural implementation of this theory is quite direct and yields the PNN’s. A PNN consists of a node in layer one for each of the \( N \) training sample. The weights leading from the input to a layer one node are the coordinates of the corresponding sample. The node computes the distance \( d(s,x) \) from the test vector \( x \) to the training sample \( s \) and outputs the value the Gaussian according to equation (3). The outcome of each of the layer one cells is added separately for the different classes according to equation (2) by the connections to the output cells with weight one. Other different techniques that try to better estimate the probability density function underlying the problem at hand may be found in the scientific literature; the network structure remains the same, only the computation in the nodes changes. The Minimal Error Neural Network (MNN, [8]), the Elliptical Basis Function Network (EBF, [3]), and the Rotated Kernel Probabilistic Neural Network (RKPNN, [7]) uses a multivariate Gaussian with different covariance matrices \( \Sigma \) for each sample \( s \), that means using local Mahalanobis distance instead of the Euclidian one.

The MNN tries to separate the densities of the different classes by looking for samples of other classes. The shape of the spheres of influence is determined by extending each of them just as far as samples of other classes are reached. The size is determined by making sure that densities of different classes overlap only by a fixed percentage. The EBF just considers samples of the same class. The shape is determined by computing the local covariance of the members of the training set. The size can be defined in terms of the nearest samples that enjoy some prefixed properties (for knowing details, the interested reader please see [6]). The RKPNN works like the MNN but the way the covariance matrices \( \Sigma \) for each sample \( s \) are built-up is slightly different, in fact it exploits the local properties of the input space. Moreover, instead of using the Gaussians as basis functions for density estimation, other kernel functions can be considered.

4. Experimental results

Our experiments concern remote field eddy-current inspection data classification for defect identification [2]. The data are relative to conductive objects and are the amplitudes of complex voltages measured by a coil pair. The available measures are depicted in the Figure 1. In our experiments we used the RKPNN with the following three different kernels in substitution of the one reported in equation (3):

\[
\begin{align*}
p_{G}(s,x) &= D_s^{-0.5} \exp\left(-w((x-s)^T \Sigma_s^{-1}(x-s))\right), \quad \text{Gaussian kernel}, \\
p_{L}(s,x) &= D_s^{-0.5} \exp\left(-w((x-s)^T \Sigma_s^{-1}(x-s))^{0.5}\right), \quad \text{Laplacian kernel}, \\
p_{S}(s,x) &= D_s^{-0.5} \exp\left(-0.5 \exp\left(-\frac{1}{w((x-s)^T \Sigma_s^{-1}(x-s))^{0.5}}\right)\right), \quad \text{Sigmoidal kernel},
\end{align*}
\]

where \( D_s = \det(\Sigma_s) \), and \( w \) is a free parameters, hereafter referred to as kernel width, that controls the overlapping of the spheres of influence for each sample of the training set. The parameter with which we measure the performances of the networks is the percentage of correct classification, versus the value of the kernel width. The obtained results are depicted in the Figure 2.

5. Conclusion

The aim of this paper was to illustrate new experimental results obtained when trying to perform non-destructive testing of metallic objects by the eddy current inspection technique in conjunction to an improved probabilistic neural network structure, developed by Galleske and Castellanos [7]. Obtained results show the effectiveness of the proposed approach that allows to identify the untrained eddy current patterns with a 100% correct classification.

References


Fig.1: Available eddy-current based measures.

Fig.2: Experimental results with the four RKPNN’s. (Dashed lines = Training set classification, Solid line = Test set classification).