# Neural Network for Inverse Mapping in Eddy Current Testing


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## Abstract

*A neural network mapping approach has been proposed for the inversion problem in eddy-current testing (ECT). The use of a Principal Component Analysis (PCA) data transformation step, a data fragmentation technique, jittering, and of a data fusion approach proved to be instrumental auxiliary tools that support the basic training algorithm in coping with the strong ill-posedness of the inversion problem. The present paper reports on the further improvements brought by a new, randomly generated database used for the training set, proposed for the reconstruction of crack shape and conductivity distribution. Good results were obtained for four levels of conductivity and non-connected crack shapes even in the presence of high noise levels.*


## 1. Introduction

Eddy current testing (ECT) technique, despite its major benefits (e.g. low costs, high checking speed and robustness, sensitivity to large classes of defects) has failed to be generally accepted for industrial application. This is due to the difficulties added for the solution of the inversion problem i.e. size and shape of the detected cracks. Inversions of ECT signals to reconstruct crack shapes has mainly been based on analysis of the underlying process in so called *model-based* methods [1-3]. Problems related to complexity, or low speed, encountered in the model-based inversion approaches have suggested that *model-free* (empirical) methods could represent a good candidate to be used in hybrid or standalone schemes. Model-free methods employ rules and/or maps, determined from the whole past experience and the longer and better this accumulated knowledge, the greater the accuracy and robustness achieved. The most successful regression methods for extracting these maps are based on neural network (NN) application [4-7]. Our option, presented in previous papers [8][10][11] was for a NN architecture whose training algorithm is able to cope efficiently with some inherent difficulties encountered to other algorithms. The present work reports further improvements brought by the algorithm to generate the database for the training set and the successfully reconstruction of cracks having four levels of conductivity values.

## 2. Outline of the General Mapping Algorithm

The inverse mapping algorithm was extensively presented elsewhere [8][10][11]. The combination of a special training algorithm with incremental learning [9] and the statistical analysis and transformation of the input data – by Principal Component Analysis (PCA), together with a special data fragmentation technique, jittering and a data fusion approach ensured the optimality of the regression procedure. The network contains a single hidden layer, and additional direct connections between inputs and outputs to account for the mapping linearities. The training starts with only one hidden node, and for each training epoch a new node is created, the new input-hidden connections receive random weights and the rest of the weights are solved by a least-square minimization using singular value decomposition. This association allows the parameters (weights) of the NN to comply with increasingly detailed features of the map. The mapping starts from discovering the rough features of the input-output relationship by a hypersurface in few dimensions, and pursues by increasing the attention paid to details by gradually extending the dimensionality of this hypersurface. This process continues until the quality of the representation is optimal, *i.e.*, a necessary-and-sufficient number of parameters describe without redundancy the interpolation, by giving appropriate relevance to each input. As we mentioned, the training algorithm of the employed NN implies least-squares solutions of an over-determined equation system at each iteration (training epoch):

$$\left[\mathbf{A} \cdot f_1\left(\mathbf{A} \cdot \mathbf{W}_{ih}\right)\right] \cdot \begin{bmatrix} \mathbf{W}_{io} \\ \mathbf{W}_{ho} \end{bmatrix} = f_2^{-1}(\mathbf{B}) \qquad (1)$$

where **A**, **B** represent the input, and output training sets, respectively, $f_1$ and $f_2$, the nonlinear activation functions for the hidden and output nodes, $\mathbf{W}_{ih}$ is a randomly generated, fixed coefficient matrix, and $\mathbf{W}_{io}$, $\mathbf{W}_{ho}$ are the matrices containing the unknowns of the problem, *i.e.*, the input-output and the hidden-output interconnection weights, respectively. Also, a new regularizing feature was introduced, *i.e.*, a `cooling' procedure for the hidden nodes' nonlinearity. The steepness of $f_1$ is increased progressively -- by a logarithm-based function -- while training the network, allowing the regression to `discover' first the rough features of the error surface, and to locate smoothly its details.

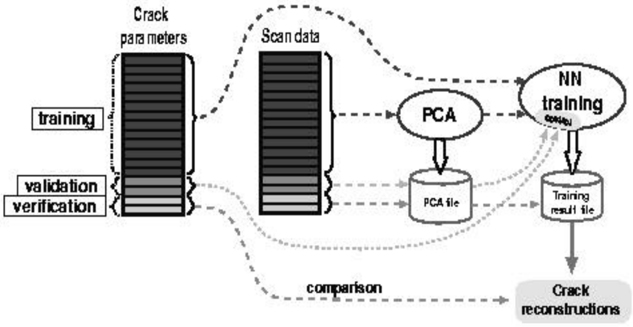



Fig. 1 Data flow through the basic inversion algorithm.

Fig. 1 depicts the data flow through this *basic* mapping algorithm. The I-O pairs of the initial database are partitioned into training, validation and verification sets. The `PCA' and `NN' modules are presented with the training data and issue the two files for later use. The PCA file is used for the transformation of both the validation, and verification sets. The validation set is used only to control the training optimality, by monitoring the currently achieved estimation error. The reconstructions are conducted on the verification set, and, if available, the corresponding `correct' shapes are compared with the estimated ones. The latter set is the equivalent to the *in situ* scan data (the `fresh' data). At this stage, the previously recorded files are employed, and only elementary operations are necessary for data transformation and propagation through the trained network. These two steps are very fast and can be performed in real-time with small computation requirements during the actual testing. Being based on learning an input-output mapping from a set of examples (the training set) or fitting in a least-squares sense a hypersurface to this set in view of acquiring good generalization properties in unpopulated points, the whole procedure is equivalent to a statistical regression. The shifting aperture technique roles are to reduce the ill-posedness of the map, to minimize the dimension of the mapping problem and to multiply the number of available cases. The rationale of the method was extensively presented elsewhere [11]. Fig. 2 depicts the shifting aperture mapping approach: each aperture from an initial full-scan is mapped onto a corresponding object window, and both are simultaneously shifted. Obviously, the optimal openings and shifting step of these scan and object fragments will depend on the frequency, scanning step, probe construction and material parameters. It was found [10,11] that equal openings -- of about the same spatial extent as the probe's active area -- and a shifting step equal to the scanning step ensure a good conditioning for the problem. After cutting and shifting the raw full-scans, the resulting database will be sent to the basic inversion algorithm -- as was depicted in Fig. 1 -- to pass through the PCA, and NN modules.

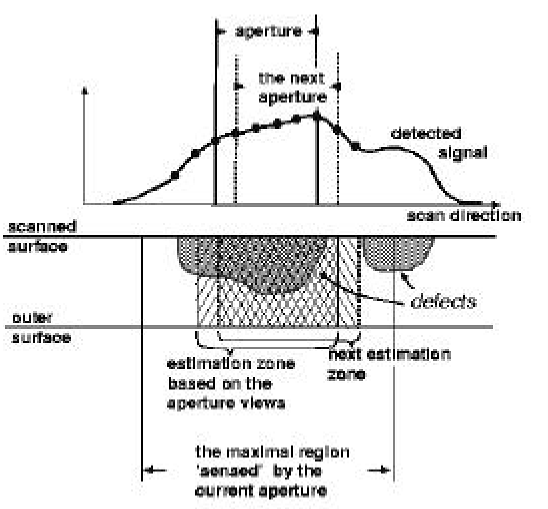



Fig 2. Shifting aperture strategy for flaw reconstruction

## 3. The database for the training set

The reconstruction quality of the trained network relies not only on the optimality of the training algorithm but also on the generality of the primary input data used for the training set. The data provided to the network are expected to contain enough useful information about the “points” of the regressed ‘hypersurface’. It should be noted that the resulted map has to be accurate only in a critical region of the problem space. Theories of fracture mechanics and results of experimental tests can be combined for deciding the critical dimensions and shape classes of propagating cracks. Based on these results, a minimal database can be constructed.

The present study shows that an improved generation algorithm for the training data could significantly enhance the mapping potential. The algorithm aims to acquire two different goals: first, to uniformly populate the parameter space of the problem with the elements of the database and, second, to reduce the generated shapes to a restrained crack shape class. For the first goal, the random character of the generation and for the second, some imposed constraints on the randomly generated parameters of the crack are effective. All cracks were supposed to be inner and superficial or having at least a zero-conductivity (air) area on the surface. The randomly generated parameters are the total depth of the crack beneath each scan point, the depth of the zone with air of the crack and the value of the conductivity in the crack cells, thresholded at four imposed levels.

In the first stage, 600 longitudinal scans were simulated along the same number of randomly shaped surface-breaking cracks in a plate specimen. An area of 20x40 mm of the specimen represented the analysis model. The thickness of the plate specimen is 1.27 mm, and the material parameters are: $\sigma=10^6$ S/m, $\mu_r=1$. A pancake-type probe at a constant lift-off of 0.5 mm was simulated for the scanning. The energizing frequency was 300 kHz. Each complete scan consisted of 21 probe readings along a probing line parallel to the crack mouth, in 1mm steps. Apertures of 5 elements, and estimation windows of 6 mm opening were taken. From the total of 600 complete, 21-points scans were formed in this way N = 600 ((21-6+1)) = 9600 such input-output vector pairs. From this maximal database, validation and verification sub-sets were extracted prior to any subsequent module of the algorithm, and used only in the testing phase.

## 4. Numerical Results

The performance measure of the regression was given by the average deviation of the reconstructed parameters for the validation, or verification sets:

$$ADev = \frac{1}{p \times q} \sum_{i=1}^{p} \sum_{j=1}^{q} \left| b_j^i - \bar{b}_j^i \right| \qquad (2)$$

where $p$ and $q$ are the number of scanned flaws contained in the testing set, and the number of parameters per entire reconstructed windows, respectively. $b_j^i$, $\overline{b}_j^i$ are the actual, and estimated output values. For these parameters we obtained values corresponding to an average per-cell deviation of less than 6%. However, a `good' average deviation value did not correspond always to a good estimation of the parameters defining the flaw peculiarities and was sometimes just an indication of a higher contrast between the colors associated to the conductivity value. As it was chosen to not threshold the outputs, the visual examination of the reconstructed shapes became equally important.

The mapping was obtained by training with unjittered signals. In Fig. 3, four reconstruction examples are presented in gray-level images. For each estimation, the correct image is given above. The training was stopped after about 200 epochs, when a minimal error was obtained for the selected validation sets. One can notice that fair reconstructions are obtained for the multiple successive cracks and for complex shape and conductivity structures. Each image represents a 20mm long profile, which is obtained by a weighted superposition of 16 successive windows.

In the same setup, the algorithm was tested on signals containing artificial injected uncorrelated (white) noise, 15% from the signal maximum. The results were not satisfactory when the map was obtained from noise-free training sets. When the data jittering technique was employed and the original signal collection was expanded two times to contain additional (5% and 15% from the signal maximum) noise levels, the map became very robust. Fig. 4 gives some examples, obtained after about 300 training epochs. For each estimation, the correct image is given above.

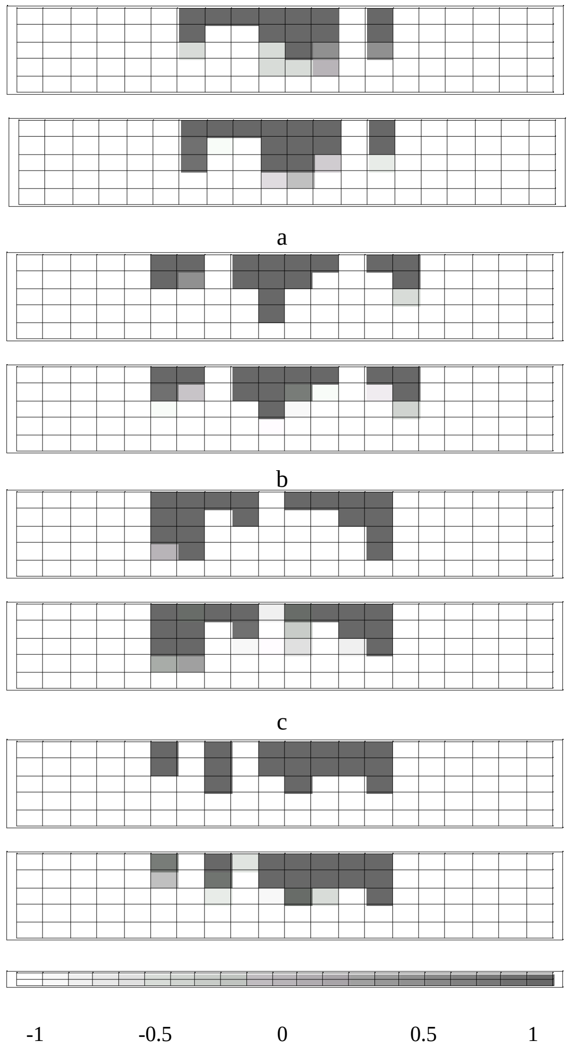
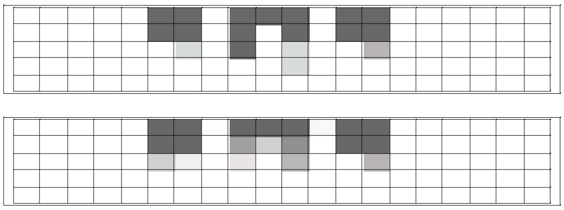



Fig 3. Reconstructions from noise-free data.

Clearly, regressing a map able to “encode” not only complex (crack) shapes, but also four conductivity levels for each composing cell is a difficult task for any algorithm. If one takes into account the small number of database’s scans and the high degree of ill-conditioning that is characterizing this inverse map, a satisfactory solution to this problem becomes unlikely, even for sophisticated NN algorithms. Here is where the role of the whole chain of procedures involved by the proposed algorithm becomes clear. Common NN auxiliary practices like data pre-processing, jittering, together with the special training algorithm employed are becoming decisive regularization tools for this particular problem. Additional, application-related procedures, like data fragmentation and shifting, data fusion and restriction of the class of training data are not less instrumental for the whole algorithm.



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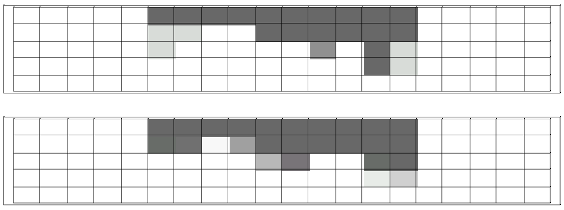

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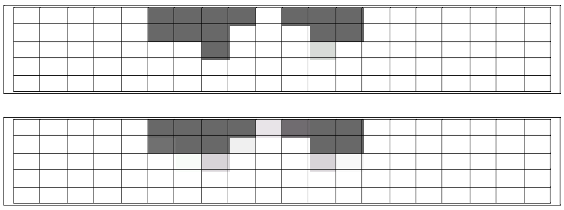

c

Fig. 4 Reconstructions from noise-polluted scan data.

## 5. Conclusions

An NN-based mapping algorithm for the inverse problem in eddy current testing has been presented. The algorithm involves a special training procedure chosen as highly suitable for the problem’s nature, feature-oriented data processing (PCA), data jittering for coping with noisy input data, an application-related data fragmentation-shifting-fusion technique and a newly added generator of training cases. The quality of the information contained in the database for the training set was found to be very important. A randomly generated database, according to the imposed patterns of the crack shape and conductivity was used. The crack shape generator allowed the database to achieve the necessary quality for coping with a highly complex inverse mapping, where each crack parameter (cell) can take four levels of conductivity. Good reconstruction results were obtained even in the case of high-level noise. The algorithm's capability of reconstructing multiply connected and unconnected crack domains is important, as this encourages the attempts to tackle the problem of natural cracks. The proposed mapping algorithm can be easily extended to 3-D reconstructions from 2-D scans.

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