Optimized Database for Crack Reconstruction by Neural Network

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Abstract. The non-destructive evaluation of in-material defects is carried out using neural network. The network is trained with the eddy current testing data measured for suitably selected defect prototypes, so that this selection constitutes a consistent representation of the forward problem. It is shown that in presence of noise this network performs in defect reconstruction better, than those networks trained with randomly or regularly selected defect prototypes of about the same number.

1. Introduction

The estimation of the parameters of cracks is a frequent objective of the eddy current testing (ECT). The forward model that allows to calculate the data measured by the ECT probe from the crack parameters in fact maps the crack parameter space to the data space. This mapping is often complex since the modelling of such ECT configurations generally requires the use of numerical methods. It results that an inverse mapping cannot be obtained explicitly. One possible way to carry out the inversion is then to build a database containing the measured data of some selected crack parameter prototypes. This database is then used to adjust the degrees of freedom of a behavioural inverse model linking the data space to the parameter space.
The selection of the database examples is of considerable importance since the consistency of the inverse model depends on them. The regular mapping of the parameter space is generally speaking not an effective solution since it does not take into account that the sensitivity of the probe is often not uniform on the whole range of the parameter space.
In this paper we present a database generation method based on the meshing of the parameter space with elements whose node degrees of freedom contain the measured data of the actual crack prototype [1]. We attempt to find an optimal sampling of the forward operator, such that the interpolation error of data retrieval is kept below a prescribed bound all over the model space, while using the lowest possible number of data points. The optimization of the database is carried out in the framework of an adaptive meshing. First an initial mesh is spanned over the acceptable region of the model space using a coarse uniform sampling. Then it is being successively refined by inserting new data points into the mesh (where needed) until the criterion on interpolation error satisfies everywhere. Note that we use directional refinement based on edge bisection technique, which may result in a so-called anisotropic mesh. This procedure acts as a systematic exploration of the model space and allows the examples to be more concentrated in the high-sensitivity parameter regions of the probe. The resulting database is referred as optimised mesh database.

The reconstruction of model parameters from the measured data requires backward search in the database. Nearest point search algorithms can be used for this purpose, but often they are too slow to meet the requirements of industrial applications. A faster alternative is to use a neural network (NN) having universal and parsimonious function approximation capability [6]. Indeed it is capable to "learn" a set of training input-output pairs, and then can be used to predict the output for an input that is not contained by the training data set. All this is done without referring to the underlying complex physical phenomena which it is intended to model. However, the quality of this prediction depends very much on the consistency of the chosen training data set.
This paper presents an application of the optimal mesh database approach combined with neural network for crack reconstruction. An application is considered showing that - in the case of the same number of examples - NN trained with a mesh database performs better in crack reconstruction than NN trained with regularly selected prototypes. As a consequence, it is possible to minimize the size of the database to be generated and to reduce the related computational and financial costs. Although the idea is demonstrated here through a particular problem of NDT, the concepts and algorithms introduced are applicable to a much wider class of inverse problems.

2. Description of the considered problem

The study is based on a JSAEM benchmark problem [2]. A coil-probe scans above a conducting plate having a crack (Fig. 1). The impedance variation of the coil is measured at some regular positions for a frequency of 150 kHz.

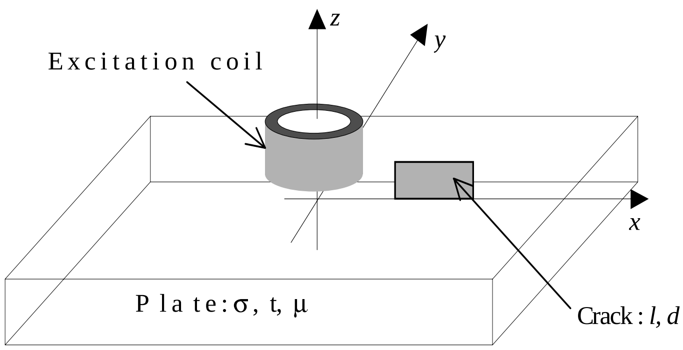
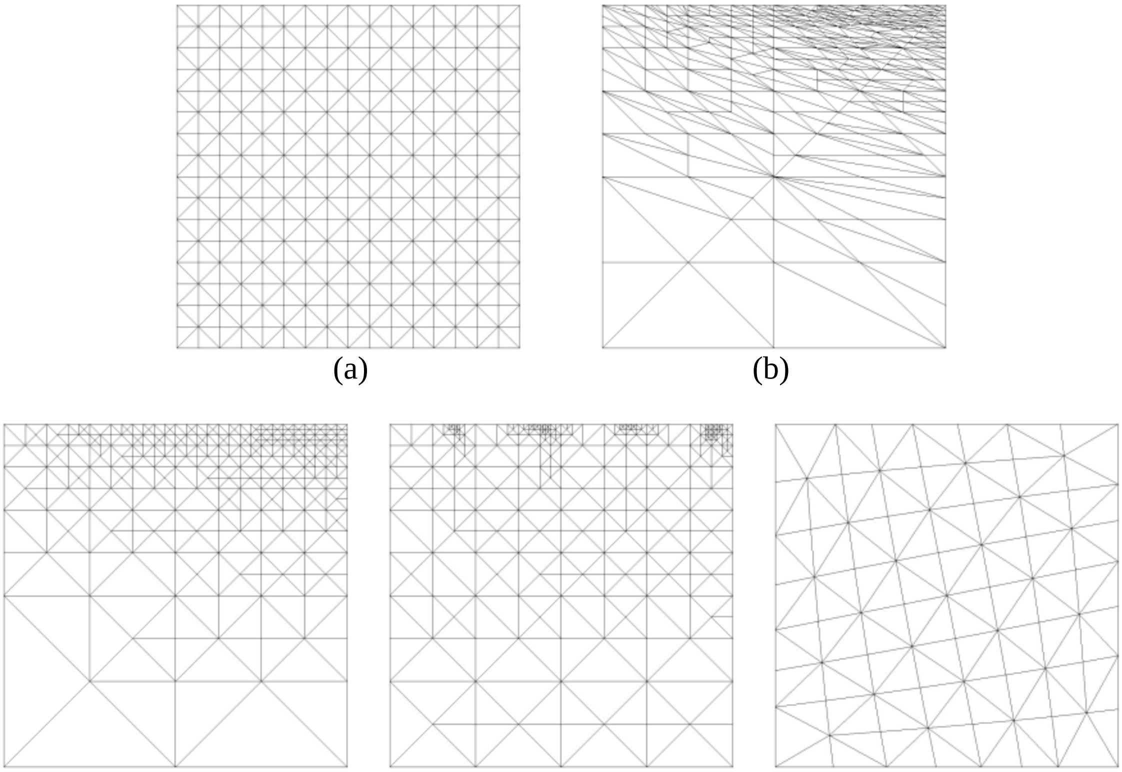


Fig. 1. Considered problem

The measurements are simulated using a numerical tool [3]. We limit the study to the prediction of the length (l) and depth (d) of the crack assuming that the remaining parameters (position, orientation, etc.) have been already determined with other methods [4]. Both OD and ID type cracks have been considered. The probe data used for the inversion are constituted of a scan line centred and parallel to the crack. This line contains 21 points with 1 mm step. The forward operator is defined here as the mapping from length-depth parameter pairs to the 21 complex numbers of impedance variation.

3. Database generation

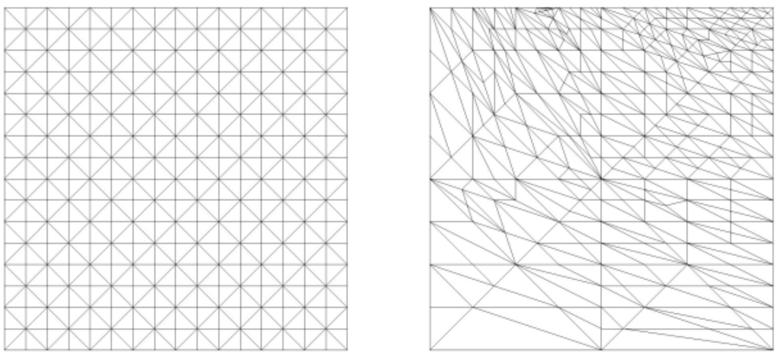
For comparison, several mesh databases have been created. All of them represent the forward operator within the length range 3-10 mm and the depth range 10-90% of the model space. They contain about the same number of data points. Fig. 2 and Fig. 3 show the location of the samples (grid points) of the different data sets in the model space (the horizontal and vertical axis are the length and depth coordinates of the model space) obtained for OD and ID type cracks, respectively. The pictures (a) show the mesh structure of a uniform sampling on a 17x17 regular grid. This database (called “regular”) plays the role of reference among the different databases used as learning sets for neural networks.



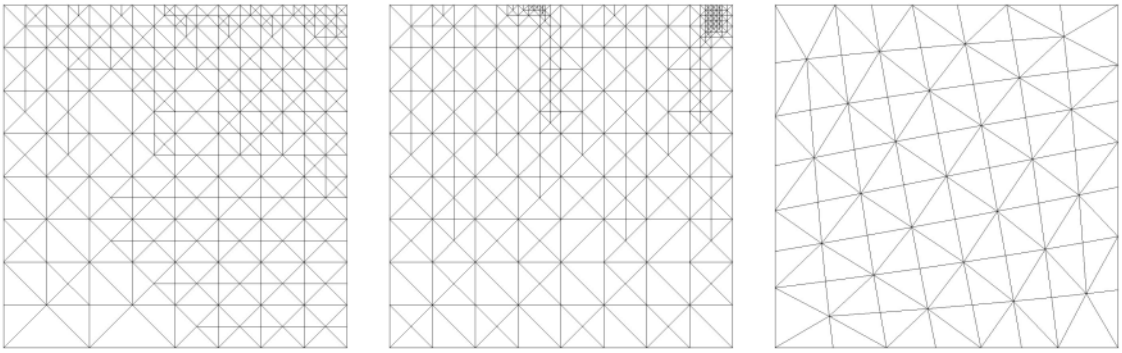
(a) (b)

(c) (d) (e)

Fig. 2. Distribution of the database examples in the parameter space for OD type cracks: uniform sampling (a); optimised for nearest neighbour interpolation (b); the same with triangle shapes constrained (c); optimised for linear interpolation (d). Test data set (e).



(a) (b)



(c) (d) (e)

Fig. 3. Distribution of the database examples in the parameter space for ID type cracks: uniform sampling (a); optimised for nearest neighbour interpolation (b); the same with triangle shapes constrained (c); optimised for linear interpolation (d). Test data set (e).

Pictures (b) show the structure plot of the database optimised for nearest neighbour interpolation. It means that the error of nearest neighbour type interpolation on this mesh is nearly equal at every locations of the model space. We refer to this database as “nearest” in the following. As database “regular” is uniform in the model space, it can be said that “nearest” realizes an approximately uniform sampling in the data space. Note that the mesh is anisotropic (i.e. it may consist of rather distorted triangles).

Interpolation on a distorted simplex is often a source of numerical errors. In order to avoid the occurrence of such simplices we may apply a constraint on good triangle quality in addition to the criterion on interpolation used in the case of “nearest”. The resulting database structure can be seen on picture (c). We call it “nearest-iso” because of the isosceles triangles in the mesh. On the other hand we do not take this database for as tight a representation of the forward operator as “nearest”, because of the artificial constraint on triangle shape.

Pictures (d) show the structure plot of the database optimized for linear interpolation. It means that the error of linear interpolation on this mesh remains around some prescribed level. As opposed to database “nearest” the error eqidistribution is not strictly realized here, because good triangle quality is constrained at the same time. We refer to this database as “linear”.

Finally pictures (e) show the data points of the test data set used for the performance analysis of neural networks trained with the above databases. The points are scattered in uniform distribution but in a way that they practically do not coincide with the points of set “regular”. The distribution of the test data could have been different if we had an a priori on the probability distribution of the length-depth parameters.

4. Crack characterization using neural network

The crack characterization is done using multilayer perceptron NN [5]. Each network is constituted of a hidden layer of hyperbolic tangent activation functions and an output layer of identity activation functions (Fig. 4). This architecture of NN exhibits universal and parsimonious function approximator properties. The network is fed with the 42 real measurement parameters resulting from the scanning of the probe (real and imaginary parts of the complex impedance variation at each probe position). It provides the estimated length and depth of the crack.

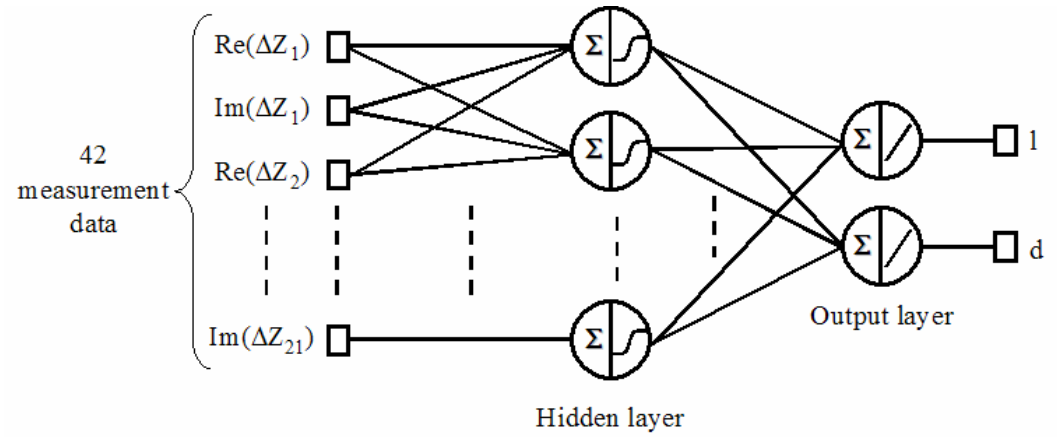


Fig. 4. General structure of the implemented neural networks

For each previously defined training data set the adjustment of the internal parameters of the network is carried out with the Levenberg-Marquardt algorithm [7]. The goal of the training is to minimize the mean square error (MSE) between the outputs of the network and the outputs of the training data set. After the training process, the capability of the network to predict new prototypes not included in the training data set is evaluated by calculating the MSE obtained on the test data set shown in pictures (e). The optimal number of neurons in the hidden layer determined by carrying out trainings for 20 networks having a number of hidden neurons in the range of 1 to 20. The one showing the lowest MSE on the test data set is selected. The performance of the best networks obtained for the different training data sets are then compared. In order to be closer to the conditions of an ECT operation a complex noise having a Gaussian noise is added on the test set. At each measurement point of the test set the standard deviation of the amplitude of the added noise is defined as a percentage of the amplitude of the signal at this point. The accuracy of the estimation of a crack parameter is characterized by the standard deviation of the discrepancy between its estimated and its true values on the test set (given in percentage). Fig. 5 and 6 show the OD estimation results obtained for length and depth, respectively.

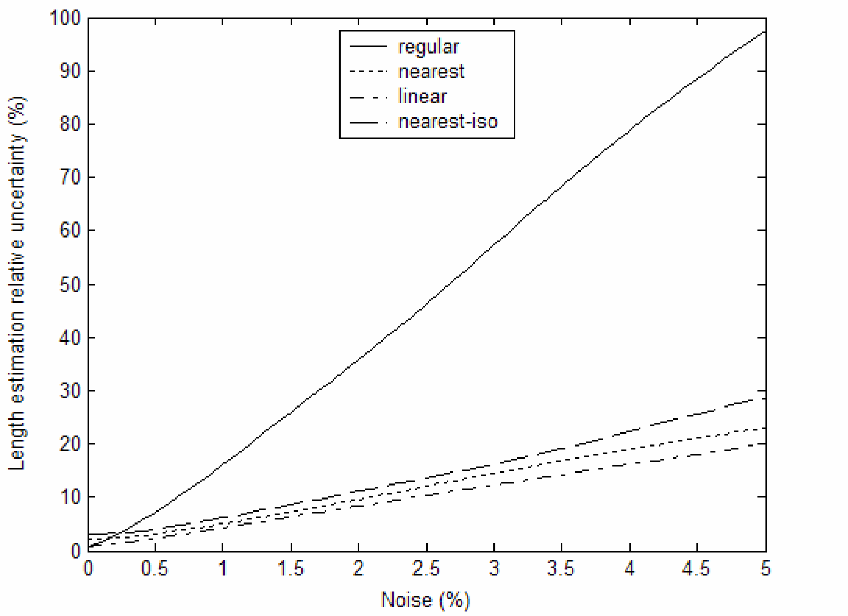


Fig. 5. Length estimation uncertainty of neural networks trained with different training sets for OD cracks

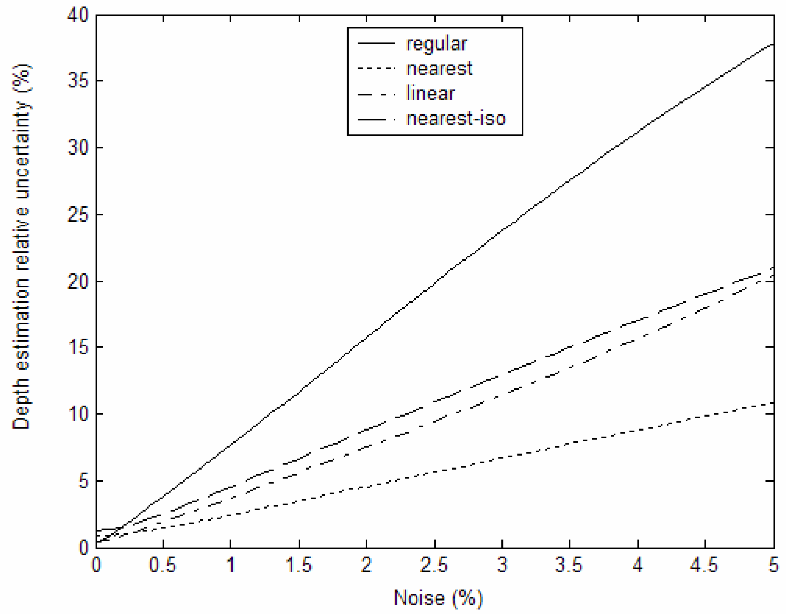


Fig. 6. Depth estimation uncertainty of neural networks trained with different training sets for OD cracks

Fig. 7 and 8 show the ID estimation results obtained for length and depth, respectively.

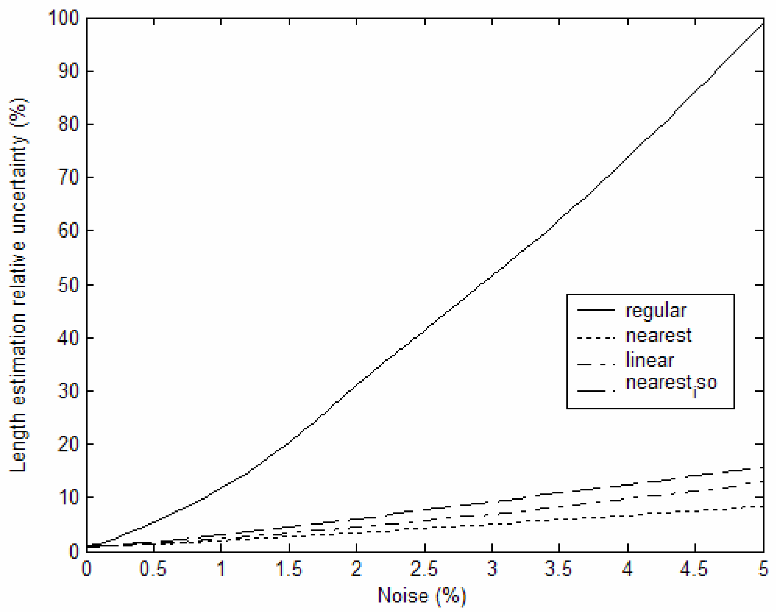


Fig. 7. Length estimation uncertainty of neural networks trained with different training sets for ID cracks

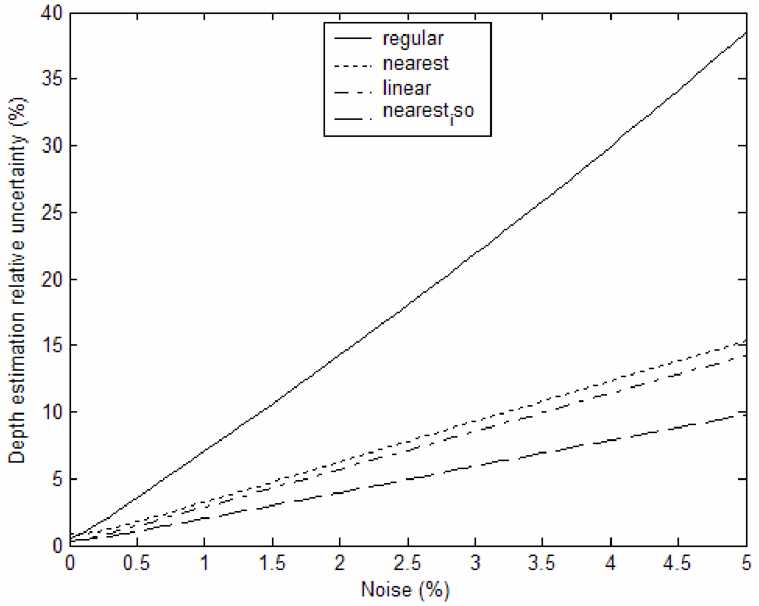


Fig. 8. Depth estimation uncertainty of neural networks trained with different training sets for ID cracks

It appears that - whatever the crack type as well as the estimated parameter considered - for a noise-free situation all the training data set lead to a negligible level of error on the estimated parameters: all of them exhibit a good generalization capability. On the other hand when noise present, the network trained with set "regular" behaves more unreliably than the other networks trained with optimised data sets. Indeed, the mesh structure of data set "regular" exhibits an ineffective density of nodes in the areas where the probe has a low sensitivity and where the noise limits the accuracy of the estimations. At the same time the mesh density of set "regular" is too weak in the areas where the probe has high sensitivity. In these regions a more refined mesh allows to reach a better accuracy, as it is demonstrated by the results of the non-uniform meshes.

5. Conclusion

This ECT inversion problem by neural network inverse model shows clearly the interest of using an optimised mesh data set for the training, especially in the experimental context of noisy measurement data. Indeed, for a defined number of data points in the training sets, a neural network trained with a mesh data set performs better in defect reconstruction than a network trained with regularly selected defect prototypes.

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