Simple Classification of mathematical simulated defects of Power plants pipelines

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Abstract
In this paper an efficient defect detection algorithm that is based on PCA (Principal Component Analysis) and MLP (Multilayer perceptron) is described. The method consists of two steps: primarily we project defects from the original vector space to an eigen subspace via PCA; secondly we apply MLP to obtain a linear classifier. The fundamental idea of combining PCA and MLP is to improve the generalization capability of MLP when only few samples per class are available. Among various methods of collecting details of pipelines, Non Destructive Testing (NDT) techniques are the most useful methods due to their efficiency and low cost. For this reason models were developed to determine surface-breaking defects along the applied field when using the magnetic flux leakage (MFL) non-destructive technique. The theoretical model fits the experimental MFL results from simulated defects. For MFL sensors, the normal magnetic leakage field is subsequently used for evaluation of defects. With regards to experimental results that is explained at the rest of this paper, The hybrid classifier using PCA and multiple MLPs provide a useful framework for the task of defect detection as well.

Keywords: Magnetic flux leakage (MFL), Non destructive Testing (NDT), Principal Component Analysis (PCA), Multilayer Perceptron (MLP).

1. Introduction
Pipelines are subject to be damaged by many kinds of defects which could not be observed by normal inspection, they are harmful to power plant system, because at least that they can cause the loss of efficiency.
The use of Neural Networks (NN) for the improvement of the defect detection of the pipeline systems has received bigger attention in the last years [1, 2]. The adjustments of the parameters used in these controllers are determined through a linear model of the system around a nominal operation point. Some techniques such as adapted control have been proposals as solution for better defect detection [3, 4 and 6]. However, the most of adapted controls is based on parameters identification on the system model and its specifications. also this paper presents a model of defects that are commonly affect pipeline systems[7-9,18-22]. In this paper two steps for the purpose of defect detection are proposals: MLP - Multi Layer Perceptron and PCA – Principal Component Analysis. The use of neural networks with parameters adjusted - table 1- prepares an accurate decision on defect or non defect purpose. at the rest of this paper collection and application of NDT database, formulation, feature extraction, recognition, classification, the employed algorithm and experimental results are discussed.
If we have a discussion to what is done before and the current approach, we would observed some of published researches that are based on the analytical model of MFL signals from magnetic charge [18-22]. But for an exception, reference [24] is just discussed a single defect. The often encountered practical situation of two adjacent defects is also discussed only by Uetake and Saito [24], but their study is limited to slots with parallel walls, of a maximum of 4mm in length. With regards to this effort that considered a multiple defect case. The
proceeding numerical modelling of MFL phenomena is exposed by Lord and co-workers [24-26]. In oppose of the significant progress made in this area to include non-linear material properties [27, 28 and 29], a quantitative relationship between magnetic leakage field and defect length has not been clearly specified. Furthermore, numerical modelling involves a direct MFL approach, since it includes predefined defect geometries and material characteristics. Calibration of the MFL signals in terms of defect depth has been studied both through finite element modelling [25, 26, 27, and 29] and through analytical methods based on dipolar magnetic charge [26,30]. Two of the numerical analysis studies [25,29] correctly predicted that the amplitude of the normal MFL signal Component increases with defect depth, and that the separation between the extreme MFL values is directly proportional to the Defect length.

In this paper, with regards to previous works, a new simple algorithm is applied that could determine defects with various shapes. For problem of encountering different kinds of defects we initializes deferent defects with five classes which each of them tries to learn a defect with determined characteristics. These features are an estimate of two large groups of defects.

2. Database of defects from MFL testing

The database of the experimental MFL signals that is employed in this project is from Applied Magnetics group (AMG) in the department of physics from Queens in Canada. This database concludes signals of MFL that measured from outside and Inside of a power plant flow pipeline. Details of this database will lead to both un annealed and annealed data plots of increasing dent depths from 3mm to 7mm, resulting in a total of 10 plots for each one.

3. Formulation of an analytical model from MFL defect measurements

If a material is magnetized near saturation, the MFL field generated by a subsurface flaw can be described as follows:

\[ H_y(x, y) = \frac{2xy(m - 2Ha^2)}{(x^2 + y^2)^2} \]  

Where \( m \) is the dipole moment per unit length this is measured as follows:

\[ h = 1.05 \times 10^{-34}, \quad m = \frac{\sqrt{3}}{2} h \]  

Where \( h \) bar is the plank coefficient, \( Ha \) is the applied magnetic field that is 1 Tesla [6] and \( a \) is the radius of the defect [7, 8]. If the MFL on the surface of a sample is calculated, the variable \( y \) is constant and is equal to the depth \( h \) of the defect So the magnitude of \( h \) could specify the depth of defect. As mentioned above, it is not necessary to get physical information, like size or position of the defect. If the unknown system and material properties are defined in \( p = 2h(m - 2Ha^2) \) and \( q = h^2 \) parameters we obtain so the following simple fit function for the MFL on the surface of a sample could be illustrated as below:

\[ f(x) = \frac{px}{(q + x^2)^2} \]  

In the developed device the signal is measured by induction coils and for this reasons the measured signal is the derivative in \( x \) direction times the velocity of \( f(x) \) of measuring device. With regards to the previous equation, the MFL signal becomes as below. In this relation we try to calculate the rate of measured signal in time. So with acknowledge of velocity, that is rate of measuring device distance in time, and by timing this term to deviation of \( f(x) \), we could reach to rate of delta f to delta t that is rate of depth in time.
\[ F(x) = v \cdot f'(x) = v \left( \frac{p}{(q + x^2)^2} - \frac{4px^2}{(q + x^2)^3} \right) \]  \hspace{1cm} (4)

On the assumption that the velocity is constant, a new parameter \( P \) can be defined as:
\[ P = \nu \cdot p = 2hv(m - 2H_a a^2) \]  \hspace{1cm} (5)

in this paper defects with radius of 0.0015m and 0.002m are mentioned with depth of 0.003m till 0.006m.

4. Feature extraction for recognition

PCA is a well-known statistical technique for feature extraction. Each \( M \times N \) MFL signal in the training set was row concatenated to form \( MN \times 1 \) vector \( x_k \). Given a set of training signals \( \{x_k\}, k=0, 1, \ldots, N_T \) the mean vector of the training set was obtained as [31].
\[ \bar{x} = \frac{1}{N_T} \sum_{k=1}^{N_T} x_k \]  \hspace{1cm} (6)

A \( N_T \times MN \) training set matrix \( X = \{x_k - \bar{x}\} \) can now be built. The basis vectors are obtained by solving the Eigen value problem:
\[ \lambda = V^T \sum_i V \]  \hspace{1cm} (7)

Where \( \sum_i X X^T \) is the covariance matrix, \( V \) is the eigenvector matrix of \( \sum_i \) and \( \lambda \) is the corresponding diagonal matrix of Eigen values. As the PCA has the property of packing the greatest energy into the least number of principal components, eigenvectors corresponding to the \( m \) largest Eigen values in the PCA are selected to form a lower-dimensional subspace. It is proven that the residual reconstruction error generated by discarding the \( N_i \)-m components is low even for small \( m \) [32].

As has been said, PCA computes are the basis of a space which is represented by its training vectors. The basis vectors computed by PCA are in the direction of the largest variance of the training vectors. These basis vectors are computed by solution of an Eigen problem, and as such the basis vectors are eigenvectors. These eigenvectors are defined in the signal space. They can be viewed as signals and indeed look like its inherent shape. Hence they are usually referred to Eigens.

4.1 Recognition of defects

The recognition of power plants flow pipeline corrosion defects in this paper includes pre-processing and classification analysis. The former can be accomplished by recognizing and classifying typical features of signals from magnetic flux signals in types of mathematical forms. An approach is to classifying and performing a liable decision. For this reason, these are a both Multilayer Perceptron (MLP) neural networks however other procedures like Learning Vector Quantization (LVQ) [10], Self Organized Machine (SOM) [10] are approaches for classification. In this work multilayer perceptrons are applied with sigmoid transfer function and back propagation algorithm.

4.2 Classification for recognition

According to construction of combiners, they are all made of learning process. Therefore to have different combiners different ways of training is essential. The process of learning is based on many ways such as: different ways to show inputs, samples for learning, training
process, differ consulting technologies although in this task many theories are offered but each of them should due to some results:

1. The first requirement is that each expert has high level of performance and independently in deciding feature.

2. Expert has an arithmetic mathematics table to refer this point as strong point of each expert.

Classifying is done by many ways such as: multilayer perceptron (MLP), radial basis function (RBF), k-mean etc.

This paper presents MLP for classifying. MLP means multi layer perceptron. Classifying is done by neural networks such as MLP.

Fundamental work of MLP is to changing weights between layers and each layer has \((m)\) nodes. Number of input nodes is depended on dimension the database. Amount of nods located in hidden layer are subject to change by complicated rate of the expert. In this paper an approach is shown in follows that specifies the number of each layer this equations for this reason is earned experimentally but the result of this employment is satisfied. In training situation the weights are subject to change until reaching the best weights. The number of training situations is determined by the number of epochs it is kept done until less mistakes appears in output.

In this algorithm five Networks with the names of MLP1 up to MLP5 are employed. these experts are learned by a same set of database and the result of classification is disposed in table\(1\).

5. Employed algorithm

![Devised algorithm](image)

We have applied similar algorithm to SSCE [1, 2 and 12] to database of MFL signals. In this Map we apply pre-processing to the crude data. this section is discussed and as a brief it contains extracting different kinds of defects from physical formulation and normalization then two classes perform a decision on the their inputs, the rate of each of which is composed by a voter to achieve a well decision. See fig. 1.

6. Results and discussion

In order to investigate the statistical distribution of the error rate, five neural networks with the same structure and transfer functions (but with different number of neurons that are referred to initial state) were trained with the same data set [13, 14 and 15]. Then the accuracy rate of each network is calculated. To calculate different numbers of hidden neurons and epochs of network training as their parameters were tuned and compared to the network described in table1. in this table AR conveys Accuracy rate, HN is the number of Hidden Neurons and TE is Training epochs. All these evidences are recorded as the best result on 10 times running of related neural network.
7. Conclusion

With regards to the last paper on this application [1], a simple algorithm is proposed for defect detection in Non-destructive testing by MFL signals. An analytical model is employed to account defects of power plants flow pipelines. That was to have an appropriate MFL profile with the defect dimension along an impregnating magnetic field. The efficiency of the model was confirmed through experimental results in MFL defect detection that is discussed in historical discussion. A clear advantage of the method presented here is the low number of parameters that have to be considered. These later are subject to recognize. For the reason of fast and facility of simulation, five expert systems were learned to recognize the request. PCA is used to compress the database and provide classification on low and efficient dimensional database. The result of all are shown and discussed in table 1. Top accuracy rate in ten times running are recorded and we think could show the efficiency of the mentioned algorithm.

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