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DCT AND MLP IN THE APPLICATION OF MAGNETIC FLUX LEAKAGE DEFECT DETECTION

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Keywords: Non-Destructive Testing (NDT), magnetic Flux Leakage (MFL), Multilayer Perceptron (MLP), discrete cosine transform (DCT)
Abstract: Non-Destructive Testing (NDT) is known as a harmless technique for industrial pipeline cyclic inspection. This way tries to find out defected parts of a device used in industry with a test by means of non itself destroying. Many ways are known and employed in NDT procedure. MFL or magnetic Flux Leakage is one of well-known and so efficient ones is widely used to find out defects in metal surface. Emission of magnetic field into device surface and recording reflected emission lead to complete a database of defect and no defect for an especial task. Then mathematical equations could help to provide normalization and classification ahead. Defect and non-defect detection are an essential and cost loss technique for analyse data from cyclic inspections. For this purpose a combination of neural networks is designed and trained in the best performance and with optimum accuracy rate. In this model Classification is done via Multilayer Perceptrons (MLP). Two level of classification is applied. First defect categorization and then defect or non-defect detection. In this paper a mathematical function named DCT or Discrete Cosine Transform is applied in pure database for data compression. This function provides a view on database in real component of frequency domain. By composing DCT function with a neural network group, this algorithm provides 97.3 percent accuracy rate in defect detection of MFL signals.

1 Introduction

Classification of defects, recognition and detection of them is a very useful and costless solution in all fields of industry. As far as 30 years ago, there becomes a try to find destroyed point of a surface without harmful ways. NDT or non-destructive testing was founded as a liable solution and non-destructive way to provide an analysis of devises surfaces. In this way many papers try to expose and design a liable algorithm to provide intelligent defect detection. This way is efficient by two main tasks. First is illustration of an intelligent algorithm and second is an exact decision without harm the main surface of device. First step in this paper is a combination of neural networks and a compression function. DCT known as Discrete Cosine Transform is one of well known ways to compress and extract main indexed data from a pure database. In this way more indexed data are collected in squared matrixes from main normalized data of NDT signals. Combination of DCT matrixes from main database is used to calculate the result and best choices are considered and reported in table 1. Output of DCT function is a compressed indexed data that is suitable to be used for classification. Two main groups of classes are combined to perform a special decision task on defect type and detection of them for a metal pipeline.

In this paper analytical functions that could simulate NDT signals achieved from surface of metal, becomes in sight of view [1].

MFL known as magnetic Flux Leakage that is presented before is one of NDT ways that focuses on return reflex of magnetic emissions on a metal surface. This way is so important and efficient to use in many fields of industry [2-10].

The other important point is nonlinear procedures that may use in intelligent algorithms. Linear and nonlinear mathematical functions help main idea to apply a more reliable and more efficient output [11-22]. This paper tries to classify defects by the rate radius however there are another way such as depth consideration [23,24].

In this paper with regards to previous approaches, performs a new combination of neural networks to provide an efficient classification on MFL database of NDT procedure [19-22]. This paper exposes two levels of networks. First step tries to find out defect type from its physical dimension and second network tries to detect defect and non-defect in final decision.

2 Database of defects from MFL testing

When a metal surface is magnetized near saturated, Magnetic Flux Leakage that reflected from saturated surface could be presented in equation (1) [2,3].

$$H_y(x,y)=\frac{2xy\left(m-2H_a a^2\right)}{\left(x^2+y^2\right)^2} \tag{1}$$

In this equation, *m* is the dipole moment per unit length and it could be calculated as follows (2):

$$h=1.05\times10^{-34} \quad m=\frac{\sqrt{3}}{2}h \tag{2}$$

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In this formula h is Plank coefficient. And H_a is the magnetic flux that applied to the surface in purpose of reflex flux measurement. This coefficient is 1 Tesla. *a* which presents the radios of defects is a parameter that is very important in our paper calculation. This value is further more used as fundamental task of this paper algorithm and classification. [11-13]. In this paper *y* is constant and is equal to the depth of the defect that is mentioned *h*. therefore magnitude of *h* specifies depth of defect. Also by some nominations to equations, *p* and *q* could be summarized as $p=2h(m\text{-}2H_a a^2)$ and $q=h^2$ therefore equation number 1 is summarized and exposed in equation (3):

$$f(x)=\frac{px}{\left(q+x^2\right)^2} \tag{3}$$

In measuring devises the story is a bit different. First inducted coils emit a magnetic flux to the surface via coils and then reflected signal is recorded. Therefore production of device velocity and derivation of *f(x)* in *x* direction is recorded. So MFL signal is exposed in equation (4).

This way could expose a view for MFL signal in time and direction. However in this way and in follow dept of defects could be considered.

$$F(x)=v\cdot f'(x)=v\left(\frac{p}{\left(q+x^2\right)^2}-\frac{4px^2}{\left(q+x^2\right)^3}\right) \tag{4}$$

3 Compression by DCT

Discrete Cosine Transform, DCT, is a Fourier based function that when applies to a pure matrix, gathers more information in first its elements. Therefore components of DCT matrix which are located top left are denser in information collected from a pure matrix. DCT is natural shaped square and when anyone wants to use a part of this matrix as for compression purpose, then should select a square matrix from top left.

Discrete Cosine Transform could be known as a part of Discrete Fourier Transform (DFT), DFT has two main parts. One is a Cosine function and another is sinus function and this can be said that DCT, is a main cosine part of DFT. This main part is made up of real components of a DFT with an even function in purpose. This function (5) is a strong function in data compression and sometimes called “energy compaction function”. This property is a ppoint to use this function in signal processing as a liable and an effort able tool [4].

$$X_k=\sum_{n=0}^{N-1}x_n\cos\left[\frac{\pi}{N}\left(n+\frac{1}{2}\right)k\right] \tag{5}$$
$$k=0,\dots,N-1$$

For our reason this function is employed because if its strong behaviour on collecting the important information in low frequencies at the top left of the DCT matrix. The squared low dimensional matrixes could lead to best and rapid decisions in some cases this later could lead to the accuracy rate of 93.1% in total decession.

3.1 Classification for recognition

In this paper a combination of neural networks are used to perform a suitable and affordable decision on defect, non defect and also defect physical shape.

Two main steps are mentioned. First one is to recognize the type of defect. In this case three classes are trained to recognize three defect types. All three classes are trained at the best of efficiency with different epochs and iterations but for provide a table to compare with others all three experts should be trained at same number of iterations. So in this way may some classes not perform at the best but are adequately acceptable.

Experts here are all Multilayer perceptrons (MLP), with tansig and logsig functions in hidden layers. Experts for defect types, have one hidden layer with tansig function [17,18]. These experts are trained to recognize a defect type. And the other hand is a network with two hidden layer. Output is a node that performs a digital task. YES or NO. output could be named as defect danger or not. Two hidden layers are responsible to perform a boundary between defect shapes; dept and surface of defects are recognized and categorized by this expert. So the output performs that defect is still in range of safe or not. Whenever defect size change to bigger surface or dept, this network wills response to 0 or 1 in regard to what system required in training phase.

DCT (Discrete cosine transform) is right one step before classification that was the main goal of this research. A mathematical solution to decrease dimensions of pure MFL data. It should be notified that the pure database is normalized. One another point when using mathematical functions to compress the data is the number of attributes of that function by which selected. Many wide ranges of attributes of course perform a better accuracy in data recognition and database reconstruction but amount of software analysis will increase and this is not good in algorithm designation. So, select an efficient number of DCT matrix is another important task. This paper focuses on networks analysis and what is important and is efficient in algorithm design. Table 1 Shows result of experimental activities in training phase.

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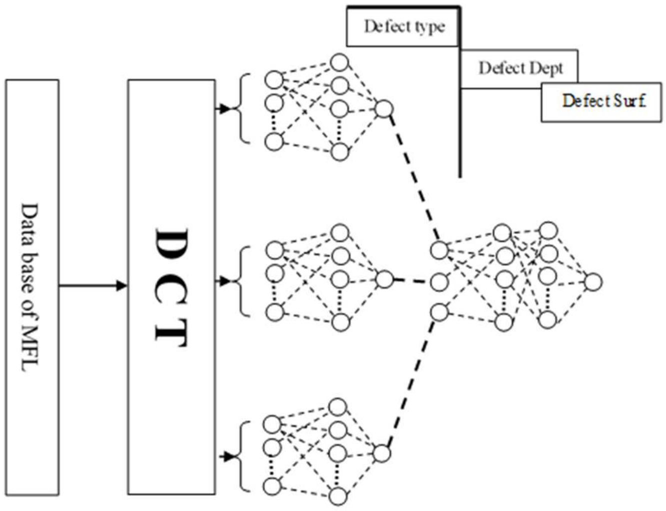

Figure 1 Algorithm scheme

3.2 *Experimental approach*

Please note that all the above quantities are approximated by less than 0.1 differences.

This table (Table 1) tries to show result and compression of algorithm shown in figure 1. Here is three networks that are feed by a database for providing a classification for categorizing MFL signals in three groups.

Table 1 Experimental research

									MAIN NETWORK →						**FINAL DECISSION**		
NET. Hidd. Layer									**NET1**		**NET2**		**NET3**				
DCT									Hidd		Hidd		Hidd		**L1**	**L2**	**RES**
								1	4	43.0	4	31.5	4	45.0	3	3	91.3
							2		5	55.0	5	40.5	5	61.3	4	4	91.5
						3			6	67.3	6	53.6	6	71.6	5	5	90.6
					4				7	73.3	7	70.1	7	77.4	6	6	89.0
				5					8	80.3	8	79.9	8	83.3	7	7	93.1
			6						7	83.6	7	80.3	7	88.5	6	6	91.3
		7							6	79.9	6	78	6	80.0	5	5	90.3
	8								5	79.3	5	77	5	77.5	4	4	91.0
9									4	77.6	4	70.3	4	72.7	3	3	91.3
5									**8**	**80.3**	**8**	**79.9**	**8**	**83.3**	**7**	**7**	**93.1**
BEST Choice																	

For data comparison, DCT is applied to database of MFL signals to compress and select valuable data indexes in DCT square matrix. DCT provides an important square matrix. But all of DCT matrix equipments will not used due to data compression. For data compression a number of squared components is selected each time and results are combined with other numbers and all are collected in table 1. For more information mentioned squared matrix in then filled with 1 to reach an acceptable dimension regards to mathematical multiplication rule. Then matrix of data that DCT is applied on it is ready to be classified in next step. Next step is classification with three classes. Class number one to three are trained to recognize defect surface of 0.000314 m2, 0.001256m2 and 0.002826m2. These defect sizes are in respect for defects of radios 0.01 m, 0.02m and 0.03m. Best result of training and test for these three classes are recorded in table 1. These results are achieved by at least 30 times training by different hidden number of nodes and the best one is recorded in table. These networks are MLP with tansig and logsig functions in hidden and output layers in respect. output layer is our final network that is designed to recognize defect from non-defect. Result shows that when defects are recognized first by three networks before, final result is better. There for at the end an overall response of network for 93.1% is achieved by the application of 7 nodes in hidden L1 and L2 layers.

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4 Conclusion

This paper introduces a simple and efficient algorithm for defect detection from MFL signals of NDT inspection. This way is based on pattern recognition and signal processing solutions. Here two main steps are defined. First data compression via DCT and second Classification by a combination of MLP neural networks. in this research, defects are categorized in three parts with focus on their surface physical shape with radios long of 0.01 m, 0.02 m and 0.03 m. neural networks in classification part are designed to work in two non-separated tasks. Defect type and defect or non-defect task. The accuracy rate of 93.1 percent totally in defect and non-defect test shows ability of this simple algorithm.

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