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An Holistic Approach to Automatic Classification of Steel Plate Corrosion Defects using Magnetic Flux Leakage

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Abstract

Magnetic Flux Leakage (MFL) technique is frequently used on aboveground storage tanks (AST) to detect volume of metal-loss due to corrosion on steel plates. Identifying the shape of detected defects in turn would lead to a better maintenance plan. Using the system described in this paper classification between three classes of defect is achieved; classes are defined depending on physical characteristics, size and shape. Signals are end-pointed and presented to the classifier in a holistic manner. The achieved accuracy is 96.7% identifying the class of emulated defects over a set of 553 recordings.

Keywords: MFL, AST, Data driven classification, defect classification, corrosion

1. Introduction

Aboveground storage tanks (AST) containing hazardous materials can developed leaks caused by corrosion of their steel floor. The main reason for storage tank failure is corrosion [1]. A recent study conducted by CC Technologies [2] shows that in the United States the total annual direct cost of corrosion on aboveground storage tanks (AST) is $4.5 billion.

A good maintenance plan is required. Inspection of a tank floor is very important as it will normally reveal the level of corrosion, the need of repair and influence the interval before the next inspection [3]. Depending upon the corrosion degree inside the tanks an inspection is to be conducted every five to ten years [4]. In order to predict and prevent leakage, non-destructive testing (NDT) is widely adopted. Magnetic Flux Leakage (MFL) is used to detect metal-loss areas due to corrosion. MFL detection tools are equipped with sensors to collect information about the state of the floor, providing information about the existing levels of corrosion. Certain defects are to be repaired in order to increase the remaining life of the tank. The repair of corroded areas can be done either by replacing the entire tank, individual damaged plates or by welding patch plates, depending on the state in which a given plate is found.

MFL can be successful in estimating the local volume of metal loss in a tank floor; however a small deep pit may give a response similar to that from a large shallow pit [3]. An automatic classifier is sought that provides information not only on the volume of a given defect but also on the shape of that defect. In turn this would help determine repair procedures and schedules. Such an MFL-based classification system is described in this paper.

2. Related work

In 1988 D.H. Saunderson [5] proposed MFL as a viable approach to tank floor inspection with the key characteristic of being rapid enough to not extend the scheduled outage time for tank inspection and maintenance. In this early work it is reported that signals were closer to percentage of volume of metal loss than to depth of pitting and therefore they might not possess enough information to characterize or classify the defects.

MFL signal depends not only on the size and shape of defects, but also on other parameters that can make classification difficult them more complicated to interpret. Qi [6] analyzes the main factors that might affect classification including the material, thickness, tool velocity, defect dimension and interaction among defects.

Some related work [5-12] indicates an increase in the use of neural networks to achieve automatic classification of defect patterns using NDT. For example, Polikar et al. [7] describes an incremental learning process aimed at the automatic identification of ultrasonic NDE signals; experimental work shows good results on 2 different data bases to solve: a) Three-class problem (inter-granular stress corrosion cracking, counter-bore, weld root), b) Four-class problem (porosity, slag, lack of fusion, crack). Other successful results in the use of ultrasonics have been reported [8, 9]. Classification of the geometrical defects cylinders spheres and plane is described by Santos and Perdigão [9] under the use of ultrasonics.

Although the scope of the work of Mukhopadhyay et al. [10] does not include experimental results on the classification of MFL signals, an interesting discussion about it is presented. It is suggested that the use of an automatic classifier to characterize metal loss defects from magnetic flux leakage signals is indeed worthy of research. The principal idea is to be able to set the nearest class from a known group to an unknown test sample, and assuming its shape and size is represented by a model. This is exactly the topic of this paper.

Ramuhalli et al. [11] estimates defect profiles by a signal inversion process realised by a neural network approach. A neural-network based approach is adopted to recover defect profiles from measured MFL signal. It is interesting because in this research work, they use a 2D-FEM model to generate the MFL signals that later are used to build and test a neural network designed to recover defect profiles. Results show an accurate estimation of the defect profile even in the presence of noise. It is to be noted that defects profiles are consistently rectangular and just the size and the level of artificial additive noise are varied.

An automatic classification of defects in pipe welds is reported by Carvalho [12]. Three classes of defects intentionally inserted in the welded bead of pipes; the corresponding signals are classified using a neural network was trained to distinguish between three defined classes: external corrosion, internal corrosion and lack of penetration. The reported success rate was 71%.

3. Signal acquisition

Every MFL machine requires two basic things: a method of magnetization and a method of detecting the leakage field. A permanent magnet is used to magnetize the inspected floor. In the machine considered here, an array of 32 Hall effect sensors is centred between the poles of the magnetic bridge as shown in Figure 1. Sensors are separated by 7.5mm. Simultaneous recordings are made from the 32 sensors as the machine moves across a steel plate. The signals are processed with an insitu micro-controller and stored on a computer via a serial connection. The sampling rate is 1024 Hz per sensor.

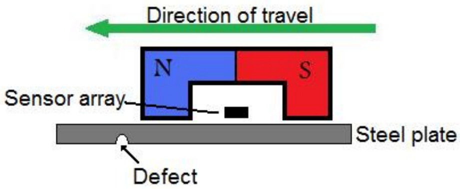
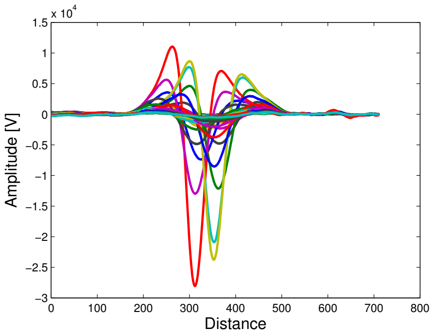


Figure 1.MFL-based scanning system with permanent magnet moved across a steel plate

Figure 2a shows the 32 signals acquired while passing over a 6mm thick steel plate that has an under floor inlaid conical defect shown in Figure 2b made by drilling the plate. The defect is 17.3mm of diameter and 4.8mm deep. Figure 2b shows an areal view.

Due to the principal design parameters namely the speed of the machine (400mm/s), the frequency 1024Hz and the relative position of the sensors (separated 7.5mm), the resolution of the motion component (horizontal) is much higher than the transversal (sensor spacing dimension) by 40 times. For illustration purposes, to obtain equivalent resolution on both axes a normalization of the signals has been carried out. This process is not applied to the subsequent signal processing. By means of equation 1 the resolution of the horizontal axe is decimated to have the same as the vertical one.

Figure 3 shows the normalized matrix of a plate with five different defects. It is to be noted that even if the resolution has been balanced the defect look elliptical as supposed as circular, this is due to the influence of MFL [13]. In order to predict any degraded area this asymmetry must be taken into account. The examples showed on Figure 3 shows a relative rate of approximately 1.6 in the vertical/horizontal axes.



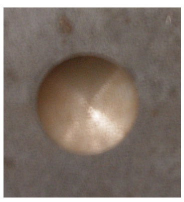


Figure 2.a) Signals obtained over conical defect, b) Defect conical with diameter 17.3mm and depth 4.8mm

$$N_{xy} = \sqrt{\sum_{i,j}^{m,n} (S_{x+i+m,y+j})^2}$$

$$where: \ m = 164 \ and \ n = 4$$

Equation 1. Normalization of signals. It is used to equalize resolution.

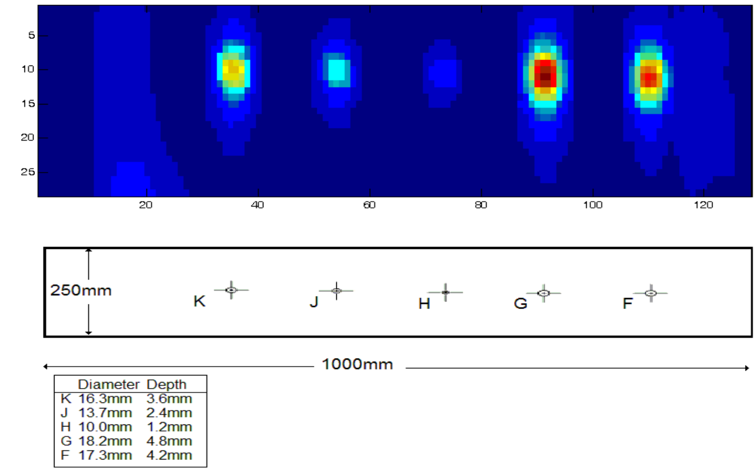


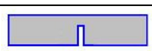
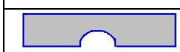
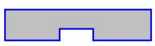
Figure 3. Normalized signals while scanning over a plate with 5 emulated conical defects.

4. Data-driven classifier

In order to classify defects due to corrosion a machine learning data-driven approach is employed. Data-driven classifiers learn from labelled data common in many speech and image recognition tasks [14].

The current MFL machine detects and locates top and bottom side defects, but it does not differentiate between them. If a defect is under the floor, no information about the physical shape and size of the defect can be obtained unless the steel plate is removed. The choice of classes to form a closed set was made taking into consideration the shape of real defects appearing in aboveground petro-chemical storage tanks. Due to the thickness of the steel platforms under consideration (between 6-12 mm) undercutting defects are unlikely to appear. Consequently here the shapes of our defects are restricted. Due to the hostile environment, to have a large quantity of labelled data from the field is difficult, thus emulated corrosion is used. To emulate corrosion several defects were made on different steel plates. Table 1 describes the shape and the size of all the used defects considered.

Table 1. Emulated corrosion. 11 different pipe defects, 9 different conical defects and 10 different lake defects

Defect profile	Defect type	Range Diameter [mm]	Range max. depth [mm]
	Pipe	2.0-6.0	2.0-4.0
	Conical	10.0-18.2	1.2-4.8
	Lake	20-100	1.0-2.0

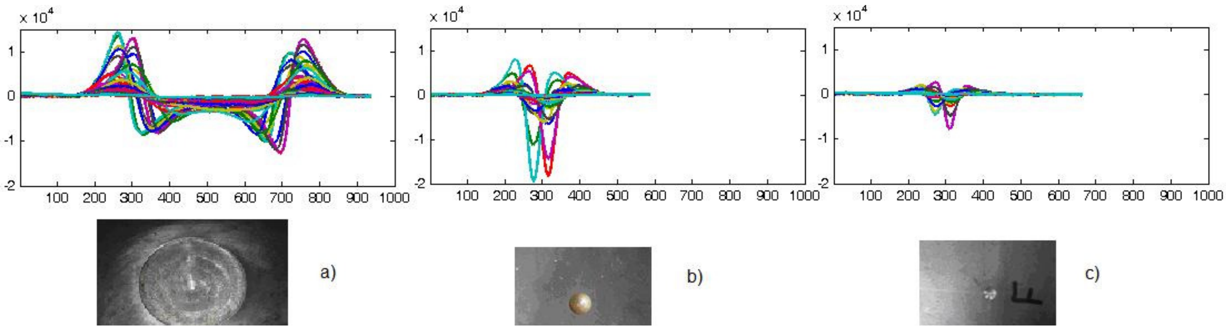


Figure 1. Signals obtained while scanning over different emulated defects also shown: a) Lake defects of diameter 100mm and depth 2.0mm, b) Conical defect of 16.3mm and depth 3.6mm, c) Pipe defect of 6.0mm of diameter and depth 4.0mm.

5. Feature Extraction

Previous works on different biometric fields [15-17] have obtained good results using a holistic feature extraction approach in equivalent multi-sensors signals. In this paper signals are first end-pointed and then presented to the classifier in a holistic manner. It is refer as holistic because all the available information from a defect is introduce in the feature vector

In order to create a feature vector 1000 samples per defect and per sensor are taken; this number has been chosen because a bigger area would represent directly a lake. If the obtained signal is smaller than the feature vector (1000 samples) then the feature vector is filled up with zeros. Sensors are organized from the most excited to the less considering their energy; the feature vector contains a total of 32000 samples covering a rectangle area of 180mm x 240mm. Due to the high dimensionality of this holistic feature vector, principal component analysis is used to distil the information content.

6. Experimental work

The overall objective of the work is to determine the class of an incoming from a finite set of possibilities, here three, after end-pointing the signal area.

6.1. The data base

The data set contains 1104 recordings of a total of 30 defects classified as: pipe (402), conical (337), lake (365). Data was captured over 11 days. The data set is divided into two groups: a) training (551 recordings), and b) testing (553 recordings). It is worth noting that there is no data overlap between the two groups.

6.2. Procedure

Experiments considering verification and identification are reported here following the scheme shown on Figure 5. The 551 samples from the training data set are used to generate three different models: pipe, conical and lake. Models are posterior tested by means of the testing data set. Each test signal is compared to the three models and as a consequence a score per model is obtained. The score indicates the probability of belonging to a model class. Thus, each test incoming signal has three scores, in total 1659 for the complete system evaluation. The performance of each model is independently evaluated using 551 set of recordings.

A support vector machine (SVM) [18, 19] is used as the classifier. Classification performance is measured by means of accuracy, equal error rate and detection error trade-off (DET) curves [20, 21].

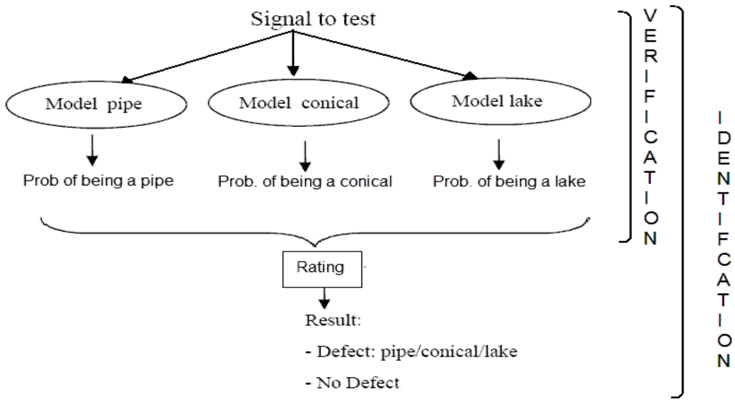


Figure 5. Scheme showing the experimental procedure

6.3. Results

DET curves are frequently used to measure the verification performance of a classification algorithm. Figure 6 shows four profiles corresponding to 4 different DET curves. The black profile corresponds to the complete system DET curve; reflecting 1659 scores, the other three profiles (blue, red and green) are linked to the corresponding single model, using 553 scores per curve. The curve shows the equal error rate (EER) for each of the models and the complete system, which are: 4.61% for pipe class, 5.37% for conical class, 0.47% for lake class and 4.16% for the complete system. Results while identifying degradations profiles are measure by accuracy obtaining a 96.7%.

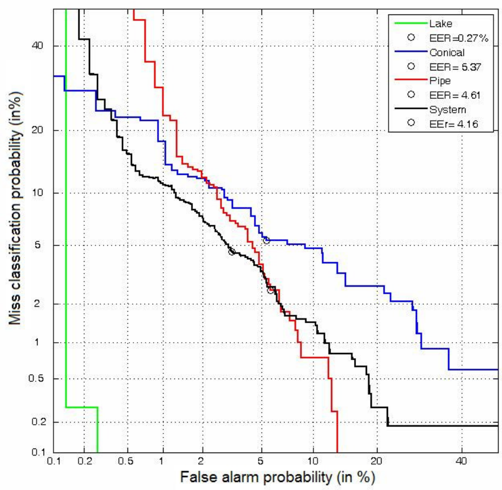


Figure 6.DET curves for experimental setup

7. Conclusions

An automatic classifier based on an holistic approach has been described in the context of defect classification given three classes (pipe, conical and lake). The system gives low error rates of 4.16 %equivalent to an overall accuracy of almost 97%. The round robin circle provide similar results, 95% of accuracy while identifying the defect, which permit us confirm that the number of samples used to train and test the models is high enough.

Acknowledgements

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