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DYNAMIC TRACKING OF DEFECTS IN PIPELINES VIA NDE BASED TRANSFER LEARNING

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ABSTRACT

Pipe infrastructure systems in service are aging and continue to degrade with passage of time. As the defects grow with time, for safety of mankind they have to be introspected continuously. Due to regular usage the inner surfaces can be inundated with tiny cavities which are not harmful and do-not need immediate repair. However, due to continuous usage these defects have to be monitored continuously so that whenever they are about to reach the pre-fixed threshold of being harmful we can repair them without delay. Here, we have developed a novel method for identification of large obtrusive defects using magnetic flux leakage (MFL) based nondestructive evaluation (NDE) technique and dynamically updated transfer learning. Running the pipeline inspection gauge (PIG) within the pipeline to collect very accurate, low noise readings for defect detection is expensive and time-consuming. The objective is to automatically detect the defective areas at the beginning and data obtained via fast inspection full of noise is estimated by mixture regression which produces posterior probabilities of the defects at each scan point. We can use transfer learning perspectives by leveraging the defect probabilities and location from the previous days, and then consequently update those probabilities based on current data by applying a dynamically updated transfer learning for properly detecting the size of the defect.

Keywords: Nondestructive Evaluation, Magnetic flux leakage, Pipeline inspection tool, Bivariate Function Estimation, Dynamically Updated Transfer Learning.

1. INTRODUCTION

Monitoring the condition and performing effective diagnosis of the defects within the pipeline has become absolute necessary as the structural integrity of the pipelines decreases due to various loading conditions with time. Over the years, various studies have been done for defect detection [1], especially using inline magnetic flux leakage (MFL) inspection technique as it provides a high resolution of the interior of the pipe from which the anomalies can be detected effectively [2]. However, there can be different kinds and shapes of defects within the pipeline, most of them are minor scratches due to passage of gas or fluids within the pipeline. Hence running the PIG every time slowly within the pipeline for continuous inspection and monitoring is time consuming and not cost effective. Our goal is to raise a flag of caution when the defect size exceeds a pre-fixed threshold beyond which they can be detrimental for usage and the pipe-sector needs to be immediately subjected to higher level manual inspection or maintenance services. In our preliminary study, defects of various sizes and shapes are simulated by a 3D finite element methods (FEM) model in ANSYS. Variation in geometrical parameters can be well simulated and understood [3].

Based on the intensity matrices, we fit a mixture regression model. The number of mixtures in the model is not fixed but determined by a data driven procedure. This allows up to well model and determine scenarios with multiple defects for intensity filed in areas with defects behaving much differently than non-defects. Here, we are running the accurate slow scan during a time when there is less or no usage of the pipeline, i.e. during regular maintenance period, from where we can detect the position of the defects with accuracy. We are referring to this day as Day 0 when the noiseless data are captured. On performing function estimation over the data received from Day 0, we can recognize the defect area accurately with ease. With that accomplished, we then run a more economic daily inspection or monitoring on the pipeline every day and data obtained is contaminated with noise. Thus, less noisy data collected once in a month is served as a transfer learning to predict the growth of the defects with time from noise prone daily scans. Since simply fitting function estimation cannot recognize the defect properly, for this reason we propose to perform dynamically updated transfer learning for defect detection under noisy condition [4].

2. EXPERIMENT

In our ANSYS model, the magnetic circuit consists of a ferromagnetic yoke, two ferromagnetic couplings and two permanent magnets [5]. Corresponding ANSYS model is presented in Figure 1. We have used the following benchmark setting as discussed in [6] to construct our model detailed description of which is given in Table 1.

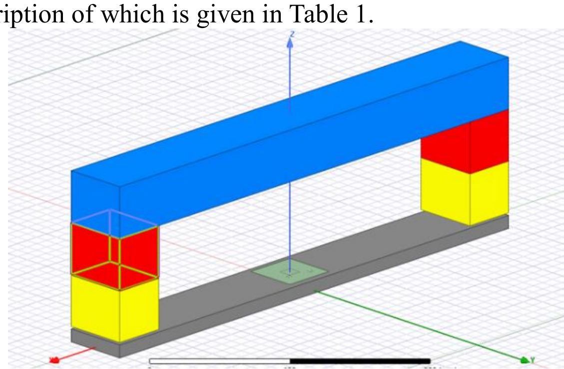

FIGURE 1: Design of the implemented Maxwell 3D model.

2.1 Transfer Learning and Data Processing

For setting up the regression model we consider the response y from 41^2 points as a vector, i.e,

$$y_i = f(x_i, y_i)\ where\ i = 1, \ldots, N^2 \quad (1)$$

and $N = 41$. x_i, y_i denotes the co-ordinates of the point for the daily probes.

Now the function f is modelled as:

$$f(x_i, y_i) = \sum_{k=1}^{K} P_k . N(\beta_0^{(k)} + \beta_1^{(k)} x_i + \beta_2^{(k)} y_i, \sigma_k^2) \quad (2)$$

The number of mixtures is K. For each mixture model, the intensity is modeled by a linear surface $\beta_0^{(k)} + \beta_1^{(k)} x_i + \beta_2^{(k)} y_i$ with aberrations having variability σ_k^2. For areas near defects, the average intensity $\beta_0^{(k)} + \beta_1^{(k)} x_i + \beta_2^{(k)} y_i$ will be different and leading to the points in those areas being from other mixing densities [7]. The mixing weight P_k can be made to depend on(x_i, y_i). While computing, for each points (x_i, y_i) we find out the posterior probabilities $\hat{\pi}_k\ (x_i, y_i)$ and based on their value can classify each point to either defective or non-defective areas. In all these cases we have observed that our function estimation matches well with the intensity plots and the defective areas can be recognized when we are applying the function estimation on the data provided by Day 0 when it is un-affected by noise. But when are adding noise to large defects as in Case 2, where we have added Gaussian noise of strength 80% to the intensity matrix of large defects then the results of the algorithm become bad. However, in this case if we can tell the algorithm the location of the defects as well as the mixing proportions then the algorithm does better. Let I_j be the intensity matrix from the Day j data. For simplicity, consider that new defects have not cropped up in between and we are connected with finding and updating the sizes of the existing defects based on I_0 as the beginning of the week or month. I_0 from slow scan informed most information about defect and location of defect will be invariant over time, while size of defect grows with time. We update the probabilities of the defects based on I_j for every j.

The algorithm is as follows:

For the daily probes for each point (x_i, y_i) do the following:

1> Mark the points in the defected area on Day 0 based on the posterior probability

$$D_0 = \{(x_i, y_i) :\ \pi_0(x_i, y_i) \geq 0.8\} \quad (3)$$

Note that the defect area based on the probe of Day 0 I_0 are points with posterior probability greater than 80% for the defective component mixture in the fitted mixture regression.

2> Note as $j \geq 1$ for the daily probes, the defective area can only grow. So the posterior probability π_0 of the points (x_i, y_i) in D_0 will not decrease.

3> For all the points in D_0 we do not change π_0.

4> For all other points at day $j = 1$ we look at points in the neighborhood of D_0. We will call a point (x_i, y_i) as a neighbor of D_0 if and only if its distance from D_0 is less than 0.1 (say). The distance of (x_i, y_i) from D_0 is

$$= min_{(x,y)\varepsilon D_0} |x_i - x| + |y_i - y| = \rho_1(x_i, y_i) \quad (4)$$

We define $\overline{D_0}$ = {all points in the neighborhood of D_0 as defined above.}

Similarly, we can define,

$$\overline{D_j} = \{(x_i, y_i) :\ \rho_j(x_i, y_i) \leq 0.1\} \quad (5)$$

where $\rho_j(x_i, y_i) = min_{(x,y)\varepsilon D_{j-1}} |x_i - x| + |y_i - y|$

5> Update the posterior probability as follows:

Consider the scan point (x_i, y_i) which is a neighbor of D_0. For simplicity consider only one defective area with mean $\mu_M(x_i, y_i) = \beta_0^{(k)} + \beta_1^{(k)} x_i + \beta_2^{(k)} y_i$ and standard deviation σ_M. The posterior probability for defect on Day 0 is $\pi_0(x_i, y_i)$. Let on day j, the reading at (x_i, y_i) is $I_j(x_i, y_i)$. Then update the posterior probabilities on day 1 by, Bayes rule as follows:

$$\hat{\pi}_D\ [j](x_i, y_i) = \frac{p * \Phi(\frac{a - \mu_1}{\sigma_1})}{p * \Phi\left(\frac{a - \mu_1}{\sigma_1}\right) + (1 - p) * \Phi(\frac{a - \mu_2}{\sigma_2})} \quad (6)$$

where, $p = P_D[j-1] = probability\ of\ defect\ on\ day\ j - 1$

$a = I_j(x_i, y_i)$,$\mu_1 = \beta_0^{(d)} + \beta_1^{(d)} x_i + \beta_2^{(d)} y_i$

$\mu_2 = \beta_0^{(nd)} + \beta_1^{(nd)} x_i + \beta_2^{(nd)} y_i$

σ_1 = standard deviation of defect.

σ_2 = standard deviation of non-defect.

Update,

$$\pi_D[j](x_i, y_i) = \max(\pi_D[j-1](x_i, y_i), \hat{\pi}_D\ [j](x_i, y_i)\ ) \quad (7)$$

Thus, $\pi_D[j] = \pi_D[j-1]$ if the scan point is inside D_j or is not a neighbor of D_j. It is only changed by the above formula for the points in the neighborhood of D_j.The above formula is written for general j and can be used iteratively.

6> Finally, iterate with the new posterior probability, μ_M and σ_M as j increases and the mixing probabilities as:

$$P_D = \sum_{i=1}^{N^2} \pi_D[j](x_i, y_i) \quad (8)$$

$$P_{ND} = 1 - P_D \quad (9)$$

where, P_{ND} is the probability of mixture corresponding to non-defect.

Update the defect area as:

$$D_j = \{(x_i, y_i):\ \pi_D(x_i, y_i) \geq 0.8\} \quad (10)$$

In this way we can update the grid of the daily noisy scans with the aid of transfer learning from the scan of Day 0.

3. PRELIMINARY RESULTS AND DISCUSSION

At first we have done our case studies on the data obtained from Day 0 i.e. when the scan is done accurately and is un-affected by noise. Since this is the most pivotal step of our analysis, we have concentrated on function estimation and recovery of the defects' location and size on day 0 as precisely as possible. For the process, we have considered three kinds of defects and has shown good recovery based on mixture regression technique for those defects sizes and locations. Thereafter, we show that the mixture regression method is not useful when we have noisy data, in which case using the updated algorithm for day 1 has produced encouraging results.

Case 1: Very Small Defect

Here we obtain the data from Day 0 which comprised of a very small defect which is benign. From the intensity plot, fitted function, training error the defect can be easily recognized.

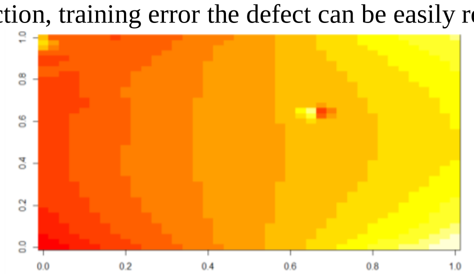

FIGURE 2: Intensity Plot of very small defect from Day 0.

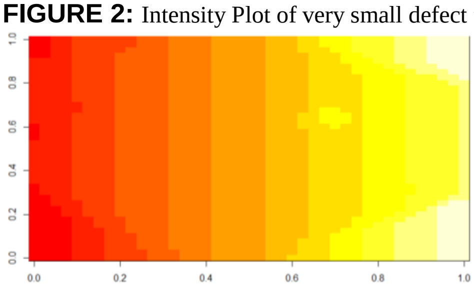

FIGURE 3: Fitted function of very small defect from Day 0.

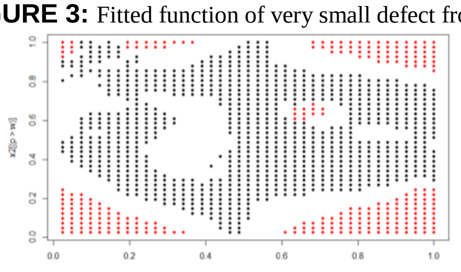

FIGURE 5: Defect area recognition of very small defect from Day 0.

From the Figure 5. we can see a very few red dots within the black dots which represent the minor scratches. Hence we can easily consider it as a non-defect.

Next, we have considered cases where the data from Day 0 consists of small and large defects. There also from the intensity plots, fitted function and training error like previous we can easily identify the growth of defect with time. Here we obtain the data from Day 0 which comprised of a small defect (say). From the intensity plot, fitted function, training error we can easily notice the defect.

Case 2: Large Defect under noisy condition

Here on Case 3 we have added Gaussian noise. This is similar to the scenario of implementing fast cheap scans within the pipeline, as fast scans are prone to be affected by noise.

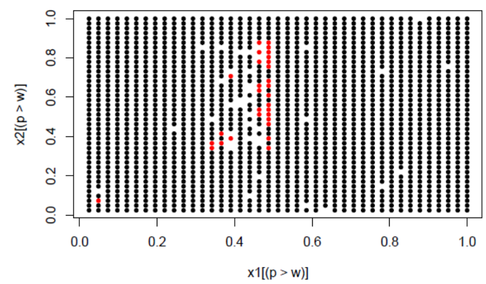

FIGURE 17: Failure of Defect detection in presence of noise

4. CONCLUSION

Hence by applying the bi-variate function estimation to the noisy data obtained from the days when the fast cheap scanning are done, then the defect size can-not be properly estimated. So to properly recognize the defect under noisy condition we are dynamically updating the grid by the auxiliary information obtained from Day 0 where the location and the size of the defect is used as a transfer learning to update the size of the defect with time. We have used **R** software to develop the above plots using **mixtools R** package.

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