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Detection and sizing of metal-loss defects in oil and gas pipelines using pattern-adapted wavelets and machine learning

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ABSTRACT

Signals collected from the magnetic scans of metal-loss defects have distinct patterns. Experienced pipeline engineers are able to recognize those patterns in magnetic flux leakage (MFL) scans of pipelines, and use them to characterize defect types (e.g., corrosion, cracks, dents, etc.) and estimate their lengths and depths. This task, however, can be highly cumbersome to a human operator, because of the large amount of data to be analyzed. This paper proposes a solution to automate the analysis of MFL signals. The proposed solution uses pattern-adapted wavelets to detect and estimate the length of metal-loss defects. Once the parts of MFL signals corresponding to metal-loss defects are isolated, artificial neural networks are used to predict their depth. The proposed technique is computationally efficient, achieves high levels of accuracy, and works for a wide range of defect shapes.

1. Introduction

Q4 Oil and gas pipelines are an important component of the energy sector nowadays. In the US, 70% of all petroleum transported in 2009 was carried by pipeline [4]. In Canada, 97% of all natural gas and crude oil production is currently being transported by pipeline [14]. However, despite being considered as one of the safest and cheapest ways to transport oil and gas [13,14], pipelines are still prone to a variety of metal-loss defects such as corrosion, cracks, and dents. These defects are mainly due to factors, such as extreme temperature and pressure inside the pipeline, exposure to highly corrosive chemicals, water, etc. The repercussions of not detecting and repairing such defects on time can be very serious: huge financial losses, damage to the environment, health and life hazards, etc. Given the size of an average pipeline, and the amount of data generated from magnetic scans, relying on human operators to sift through the data and find defects is a highly challenging and error-prone task.

This paper describes a solution to automate the process of inspecting MFL data [16–18] generated through the scanning of oil and gas pipelines. The proposed solution uses a technique based on *pattern-adapted wavelets* [15,36] to detect, locate, and estimate the length of metal loss defects along the pipeline. Once a defect is located, a number of features are extracted from the corresponding MFL signal. Those features are then fed into an artificial neural network which returns an estimate of the defect depth. The obtained depth and length are then used to assign a severity rating to the detected defect, and decide whether or not urgent repairs are due. The severity rating is assigned using industry standards such as ASME.BG31 [3], which provides a formula to evaluate a defect's severity given its dimensions, the operating pressure inside the pipeline, and other properties of the steel used to build the pipeline.

Related work. The development of techniques to assess the safety of oil and gas pipelines has attracted the attention of many researchers over the last several years [17,18,46,41,51,20,39,50]. Results on this topic are very diverse in terms of what they achieve, the specific problems they address, and the approaches they use. Fig. 1 provides a high-level summary of the research landscape in this area. Following the notation in Fig. 1, we can divide the literature on this topic into three main groups:

Group I. Numerical techniques to determine defect sizes.

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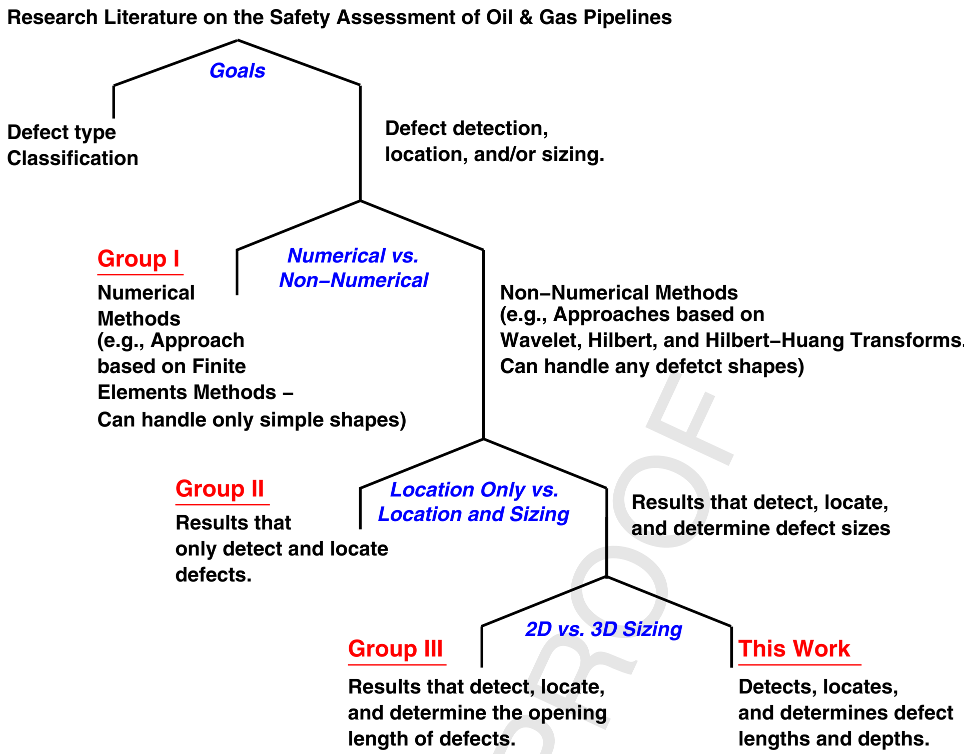

Fig. 1. Summary of related work and comparison to this paper.

Group II. Non-numerical techniques to detect and locate defects (sizing problem not considered).

Group III. Non-numerical techniques to detect, locate, and determine the opening length of defects. Some of the work in this category does also provide ways to classify defects and other pipeline features into different types (e.g., holes, valves, junctions, etc.).

It is worth noting at this point that work listed under Groups II and III includes cases where the application domain is not related to oil and gas pipelines. Some of the techniques, for example, relate to the detection and location of defects in underground power cables. In some cases also, the signals being analyzed are not MFL signals (e.g., electrical, acoustic, and pressure wave signals). None of the non-numerical methods found in the literature considered the problem of determining defect depths.

In the following, we summarize each of the group of techniques listed above, and show the similarities and differences with the work in this paper.

Group I: Numerical techniques to determine defect sizes. The work in [17,18,46] considered numerical methods, not based on wavelets, to address the problem of defect sizing from MFL signals. These methods however only apply to defect shapes for which analytical models are known. The approach proposed in [17,18,46] is to express the relationship between MFL signals and defect geometries through an equation of the form:

$$\mathbf{B}_{\mathrm{MFL}} = \mathbf{F}(\mathbf{D}) \tag{1}$$

where $\mathbf{B}_{\mathrm{MFL}}$ denotes the MFL signals, $\mathbf{D}$ is the defect geometry, and $\mathbf{F}(\cdot)$ is the analytical model describing the behavior of the MFL signals in relation to the defect geometry. Determining the size of a defect, then, reduces to inverting Equation (1) and finding $\mathbf{D}$ given $\mathbf{B}_{\mathrm{MFL}}$ and $\mathbf{F}(\cdot)$. This approach is straightforward, but has a number of limitations: (i) Eq. (1) may have several solutions, which could lead to several plausible defect geometries; (ii) solving Eq. (1) has a high computational cost – at least cubic in the size of the MFL signals matrix $\mathbf{B}_{\mathrm{MFL}}$ [29]; and (iii) the analytical model $\mathbf{F}(\cdot)$ itself is not always available. In fact, apart from a limited number of simple defect shapes (e.g., cylindrical, spherical, spheroidal, and cuboidal [18,46,29]), analytical models for general arbitrary defect shapes are still hard to derive [18,46]. This is due to the fact that deriving analytical models requires solving Maxwell's equations of magnetism [1], which is not easy for defects of general arbitrary shapes.

The authors in [17,18,46] demonstrate their approach on a number of simple defect shapes, and solve the sizing problem using techniques such as the finite element method (FEM) [48], linear algebra, and machine learning. However, as explained above, it is hard to apply this approach to defects of arbitrary shapes.

More recently, the authors in [42] have used numerical methods to study the relationship between MFL signals and defect geometries (length and depth). They conclude their paper by confirming the non-linear nature of the relationship between MFL signals and defect geometries. They do also point out the difficulty of using numerical methods for determining defect depths from MFL signals, since several defect geometries can lead to the same MFL signal characteristics (e.g., maximum peak amplitude).

Building on the observations of [42], the work in [44] uses numerical methods to estimate the worst-case defect depth corresponding to a given MFL signal. The proposed method is applied to an MFL model generated from a non-linear FEM approximation. The authors conclude by pointing out that the accuracy of the worst-case defect depth depends on the quality of the MFL model being used, and that for defects deeper than 70% of the wall's thickness, the solutions found by their method may not be correct.

Finally, the work in [27] describes a model to estimate defect depths as a quadratic function of the MFL peak values. The parameters of the model, however, are obtained by computing an FEM approximation of the MFL field for a given defect shape. The experimental results reported by the authors show that their method

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