DEFECT SIGNAL ENHANCEMENT IN INSPECTION LINES BY MAGNETIC FLUX LEAKAGE

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ABSTRACT. The detection of flaws that involve 5% or more of the pipe wall thickness is not easy to achieve for internal defects inspected from the outside. In this work we focus on a relatively straightforward technique, based on obtaining the characteristic signature of relevant defects, and projecting the actual signals on these “standard” defect configurations, thus increasing the signal-to-noise ratio and providing an alternative way to determine the nature of the defect. Several options are discussed, including some that are computationally less demanding, and are susceptible of being implemented on-line.

INTRODUCTION

Magnetic flux leakage (MFL) is one of the preferred techniques for nondestructive flaw detection in ferromagnetic materials [1]. It is used as one of the basic tools in steel pipe inspection at the manufacturing plants, where it has to be carried out at a pace compatible with the plant productivity, and is usually implemented by comparing the peak-to-peak signal amplitude with a predetermined threshold. In this application, it is usually necessary to detect very small flaws in the pipe wall, such as those that affect 5% or more of the wall thickness [2]. For thick-walled tubes and internal defects inspected from the outside, this 5% detection is difficult to achieve because of the presence of noise of comparable magnitude. As a consequence, a sizable fraction of the number of tubes has to be sent for manual inspection by magnetic particles, with the consequent productivity loss.

Several alternatives involving filtering and other approaches such as neural-net based recognition have been proposed to improve the performance of this inspection [3-4]. In this work we focus on a relatively straightforward technique, based on obtaining the characteristic signature of the relevant defects, and projecting the actual signal on these reference defect signals.

REFERENCE SIGNALS

The detection thresholds are set at calibration time, before a given batch of tubes is inspected, and are based on the signals recorded from notches machined on a calibration pipe. Figs. 1-2 show such signals, one from an “external 12.5%” notch, (i.e., from a notch...
machined on the external surface, whose depth is equal to 12.5% of the pipe wall thickness), and the other one from an “internal 12.5%” notch. It is clear from the figures that signals from external notches are larger than those from internal ones of comparable size. This is of course not surprising, because the inspection probes are located at a small distance from the external pipe surface, and are therefore much closer to an external flaw than to an internal one. Besides, it is clearly seen from Figs. 1-2 that signals from external flaws are also narrower than those from internal ones. These features imply that: 1) different thresholds have to be used depending on the nature (external/internal) of the flaw; 2) the determination of whether the defect is external or internal has to precede the decision of whether it is likely to surpass the maximum admissible defect size. The algorithm discussed below is an attempt at facilitating the detection and sizing of defects by simultaneously increasing the signal-to-noise ratio and providing an alternative way for determining the nature of the flaw.

**SIGNAL PROJECTION**

In an environment in which the analog signals picked up by the inspection probes are digitized, a defect signal is an N-component segment of a data string, and may be thought of as a vector \( \mathbf{u} \) in an N-dimensional vector space that we represent as

\[
\mathbf{u} = [u_1, u_2, \ldots, u_N]
\]  

The components of this vector are the evenly sampled values obtained by digitizing the analog defect signal.
Following a standard mathematical notation, the scalar product of two vectors \( \mathbf{u} \) and \( \mathbf{v} \) is
\[
< \mathbf{u} , \mathbf{v} > = u_1v_1 + \ldots + u_Nv_N
\]  
(2)
and the vector norm is defined to be
\[
\| \mathbf{u} \| = < \mathbf{u} , \mathbf{u} > ^ {1/2} .
\]  
(3)
The “cosine of the angle” between two signals \( \mathbf{u} \) and \( \mathbf{v} \) is therefore given by
\[
\cos(\alpha) = < \mathbf{u} , \mathbf{v} > / \| \mathbf{u} \| \| \mathbf{v} \| .
\]  
(4)
If \( \mathbf{D} \) is the vector associated to a given reference signal, the normalized reference signal is
\[
\mathbf{D}^* = \mathbf{D} / \| \mathbf{D} \| .
\]  
(5)
The projection of a signal \( \mathbf{u} \) in the direction of defect \( \mathbf{D} \) is just the scalar product \( < \mathbf{u} , \mathbf{D}^* > \).

**STRING PROJECTION AND NOISE REDUCTION**

In this context, the data string generated by a given probe may be denoted by the indefinite sequence of the evenly sampled data values:
\[
S = (..., s_n, s_{n+1}, s_{n+2},...)
\]  
(6)
and we may construct a “projected” string \( S_D \), by replacing each value \( s_i \) by the projection of the preceding \( N \)-component substring in the direction of \( \mathbf{D} \).

Thus,
\[
S_D = (..., S_{D_0}, S_{D+1},...)
\]  
(7)
with
\[
S_{Di} = < [s_{i-N+1},..., s_i] , \mathbf{D}^* >
\]  
(8)
In this way, the elements in the projected string are always smaller or equal to those in the original string, the equality holding only when the substring considered is proportional to \( \mathbf{D} \), i.e., it points in the same direction. The net result is that the signal-to-noise ratio for “\( \mathbf{D} \)-type” defects is improved when replacing string \( S \) by \( S_D \), as shown in Figs. 3-4.

Significant noise is still occasionally present in \( S_D \), i.e., there are noisy data segments that have a sizable projection in the direction of \( \mathbf{D} \), even though they do not point in the same direction, and, therefore, do not qualify as defects. To further dampen this kind of noise, we multiply the \( i \)th element of \( S_D \) by the factor

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FIGURE 3. Original data string, containing a large external defect and weaker signals hardly distinguishable from noise. The inset depicts one hundred samples, containing the defect signal.

FIGURE 4. Same data string as in Fig. 3, after projection on the external reference defect.
The final proposal is therefore to replace the string element $s_i$ by

$$S_{Di} = S_{Di} \cos^2(\alpha_i) = \langle [s_{i,N+1}, \ldots, s_i], D^* \rangle^2 / ||[s_{i,N+1}, \ldots, s_i]||^2$$

Fig. 5 shows the result of introducing this further noise reducing factor. In order to visualize better the effect of these operations on the signal-to-noise ratio, the three strings shown in Figs. 3-5 are multiplied by normalization coefficients such that the peak value of the string is in all cases equal to 1. The fact that weak signals, impossible to be singled out in the original string, are visible after being subject to this process, is precisely the point that we want to make.

**DEFECT IDENTIFICATION**

We have shown in the previous section a procedure that can be used to improve the signal-to-noise ratio in a data string. But the same procedure can also be used to discriminate whether a signal that has been extracted from one such string by any other method, is more likely to originate from a particular type of flaw. This "defect
Identification" is done by comparing the angles that are obtained by projection of the signal in the direction of the reference signals under investigation, and choosing the smaller one.

Defect characterization is an open problem, because there is a wide variety of possible defect morphologies. As an initial task, we have set the goal of discriminating between external and internal defects, even realizing that other geometrical characteristics of the flaws may mask their internal or external nature. The reason behind setting this goal is the fact – already mentioned above – that different thresholds should be used to determine the criticality of one defect, depending on which wall surface it is located. The traditional way of discriminating between these defects is based on the fact that external signals are usually sharper than internal ones, therefore having a higher average frequency, which can be determined by carrying out a FFT in real time. This is currently done at some industrial inspection lines, but implies a heavy computational burden, especially because not knowing a priori the nature of the defect, a low threshold has to be used, and therefore string segments that are candidates to qualify as defects do appear quite frequently. Alternatively, identification of signals by neural network techniques has also been attempted with satisfactory results in a study of artificial defects [4], but the problem of retraining the net every time there is a change in the inspected batch of products has yet to be solved. The advantage of the scheme proposed here is that retraining of the algorithm when there is a change in the product under inspection is fairly straightforward, because it amounts to updating the reference signal strings using the signals recorded at calibration time, which is not significantly different from the usual resetting of the rejection thresholds during the calibration procedure that precedes the inspection of each new production batch.

A final point to be considered is the choice of N, the number of elements kept in the data segments used to represent a defect signal. A fine sampling of the reference signals with N=100, such as shown in Figs. 1-2, is quite effective for noise suppression, but is likely to put too much of a burden on the CPU for on-line inspection. We were favorably surprised to realize, however, that there is no need to use all the N components of the selected segment of the input data string, and that as few as 4 or 5 conveniently chosen samples do provide a significant improvement for noise reduction and defect identification in the examples examined.

CONCLUSIONS

In spite of the wide variety of natural defects that may be present in the inspection of seamless steel pipes, we have found that the proposed scheme, based on the projection of digitized data streams on signals obtained from calibration notches, is a promising way of enhancing weak signals in a noisy environment, thus improving the detection and identification of the flaws that originate them.

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REFERENCES