

# Automatic Defect Recognition in Corrosion Logging Using Magnetic Imaging Defectoscopy Data

Rita Gaibadullina, Bulat Zagidullin, Vladimir Bochkarev

Kazan Federal University, Kazan, Russia  
{rita.gaibadullina,bulatza}@gmail.com, vbochkarev@mail.ru

**Abstract.** The Magnetic Imaging Defectoscopy is designed for detection of corrosion zones in oil wells. Location of corrosion zones is a time-consuming process, during which some defects can be missed. Therefore this process shall be automated. This document describes an algorithm of automatic defect recognition based on maximum likelihood criterion and the use of wavelet threshold processing for noise reduction and pre-conditioning of experimental data.

**Keywords:** Magnetic Imaging Defectoscopy (MID), wavelet filtering, maximum likelihood criterion.

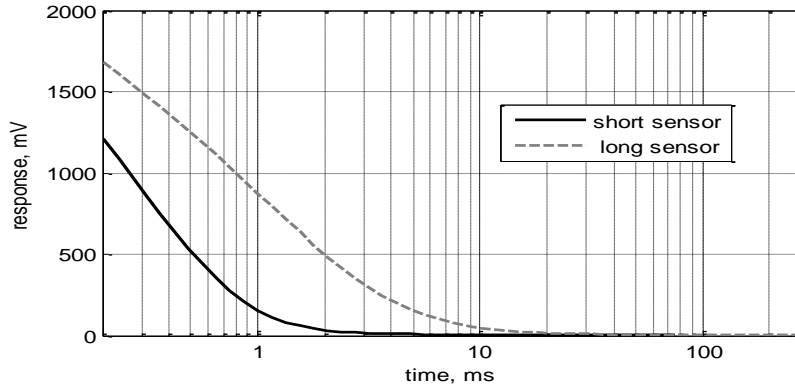
## 1 Introduction

The Magnetic Imaging Defectoscopy can be used to identify defects, corrosion intervals in oil wells. The tool generates an electromagnetic pulse and receives time-related response of tubing and casing walls. The attenuation rate of the response depends on the electromagnetic characteristics of the tube material and its thickness. Metal loss due to corrosion causes a faster decay than non-corroded metal.

The Magnetic Imaging Defectoscope (MID) contains of two sensors: the short and the long sensors. The short sensor is 120 mm in length designed to sense the tubing. The sensor generates a short pulse (50 ms) of low amplitude and magnetises basically the first barrier only, and then receives the response of 0.1 ms to 75 ms. Each decay of the short sensor consists of 42 points. The long sensor is 320 mm long; it generates pulses of greater amplitude and duration (250 ms) and takes the total response from both the first and second barriers (tubing and casing) within 275 ms. Each decay of the long sensor contains 51 points. Thus, the experimental data are presented by the 42 logs for the short sensor and 51 logs for the long sensor (Fig. 1).

Each log of the long or short sensors can be divided into the trend and drift components. The trend means a log component slowly varying with depth (can be found, for example, using a median filter). The drift means a component rapidly varying with depth, which shows deviation of real log from the trend [1].

$$A_{drift} = \frac{A(t) - A_{trend}(t)}{STD} \quad (1)$$



**Fig. 1.** Responses of the short and long MID sensors.

A DRIFT panel shall be built for visualisation of a drift components normalised to the standard deviation (STD). Generally, it is a three-dimensional graph, where the vertical axis shows the depths, the horizontal axis shows the decay time and the colour determines the signal amplitude (see Fig. 2). Gain in signal at depths of X835 ft and X820 ft corresponds to the tubing and casing collars, respectively. Gain in signal at depths of X855 ft also corresponds to the casing collars. Reduction in signal at the depth of X837 ft displays casing corrosion, which can be detected through the tubing.

Nowadays, corrosion zones are detected during well log analysis, i.e. their location is arbitrary. Moreover, the analysis of 6,000 – 9,000 ft wells consumes plenty of time, during which the defects can be missed. Therefore solution to this problem is automation of corrosion interval detection.

## 2 Automatic Recognition of Corrosion Intervals

### 2.1 Wavelet Filtering of DRIFT Data

Data are pre-filtered to remove the noise components, which could affect the performance of the recognition algorithm.

A two-dimensional wavelet decomposition is applied to DRIFT data. This wavelet decomposition is designed for processing of two-dimensional pictures with commensurable number of points in X- and Y-directions. In our case, the number of counts in the vertical axis (i.e. well depth) has an order of thousands that ten and hundred times greater than the number of values of horizontal axis (totally 42 and 51 time-related counts), therefore the two-dimensional wavelet decomposition is used first and then the one-dimensional wavelet decomposition in X-direction. The threshold value is calculated by two methods: Donoho and Birgé-Massart strategies [2, 3].

### 3 Algorithm of automatic corrosion recognition

An algorithm of automatic defect recognition includes two main steps:

1. Construction of binary maps according to DRIFT panels;
  2. Making a decision on significant deviation on binary maps;
1. Construction of binary maps using data from DRIFT panels. Statistical DRIFT data  $\xi_{t,d}$ , are converted into binary maps by some THR threshold. It is necessary to take into account that increase of the signal corresponds to the presence of collar:

$$\eta_{t,d} = \begin{cases} 1 & \text{if } \xi_{t,d} > THR \\ 0 & \text{if } \xi_{t,d} \leq THR \end{cases}, \quad (2)$$

and decrease of the signal, on the contrary, corresponds to the presence of corrosion:

$$\eta_{t,d} = \begin{cases} 1 & \text{if } \xi_{t,d} < -THR \\ 0 & \text{if } \xi_{t,d} \geq -THR \end{cases}, \quad (3)$$

2. The automatic defect recognition process is based on the decision theory. There are two hypotheses:  $H_0$  – the defect is absent and  $H_1$  – the defect is present.

$$P(x = 1 / H_0) = \alpha, P(x = 0 / H_0) = 1 - \alpha, \quad (4)$$

$$P(x = 1 / H_1) = 1 - \beta, P(x = 0 / H_1) = \beta, \quad (5)$$

where  $\alpha$  - error of first kind,  $\beta$  - error of second kind.

Each hypothesis has its likelihood function. A value of the likelihood logarithm is calculated for each hypothesis at each depth point.

The defect is absent:

$$l(0) = \sum_{t \in I} \eta_{t,d} \ln \alpha + \sum_{t \in I} (1 - \eta_{t,d}) \ln(1 - \alpha) \quad (6)$$

The defect is present:

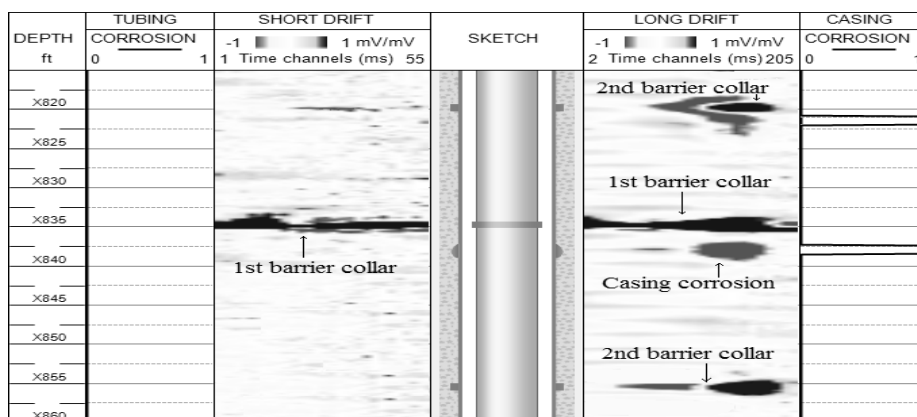
$$l(1) = \{\sum_{t \in I} \eta_{t,d}\} \ln(1 - \beta) + \{\sum_{t \in I} (1 - \eta_{t,d})\} \ln \beta. \quad (7)$$

Then the two-decision statistical hypothesis is verified by the maximum likelihood method:

$$l(1) - l(0) \geq \frac{H_1^1 C}{H_0^1 C}, \quad (8)$$

where  $\frac{H_1^1 C}{H_0^1 C} = 0$  - the decision threshold by the maximum likelihood criterion [4].

Figure 2 illustrates an example of corrosion in the casing, as the defect appears on the LONG DRIFT panel. The algorithm correctly identified the presence of corrosion and referred it to the corrosion of the first barrier, which is the tubing.



**Fig. 2.** Corrosion in the casing. Left to right: The DEPTH panel, TUBING CORROSION shows corrosion in the tubing, SHORT DRIFT is the drift panel for the short sensor, WELL SKETCH depicts well completion, LONG DRIFT is the drift panel for the long sensor, and CASING CORROSION shows corrosion in the casing.

In order to verify the algorithm, data from 11 wells were processed. Corrosions found during the well log analysis were compared with those processed by the algorithm. The following results were obtained: the automatic defect recognition algorithm accurately separates the defects of the 1st and 2nd barriers. When configuring the algorithm to search for small intervals of corrosion (metal loss less than 10%), lots of false defects are indicated, which complicates data processing. With such configuration, the algorithm detects 89% of the first barrier corruptions and 93% of the second barrier corruptions. Defects with metal loss less than 10% are not dangerous, unlike major defects with metal loss greater than 10%. The algorithm is designed to find major defects. When setting the appropriate algorithm parameters, all defects, including a small number of false defects, are detected. Thus, the automatic defect recognition allows quick identification of probable corrosion zones, on which the well log analyst should focus. This, in its turn, increases the speed and quality of data interpretation.

## References

1. Arbuzov, A.A., Bochkarev, V.V., Bragin, A.M., Maslennikova, Yu.S., Zagidullin, B.A., Achkeev, A.A., Kirillov, R.S.: SPE 162054 Memory Magnetic Imaging Defectoscopy (2012).
2. Mallat, S.: A wavelet tour of signal processing. PP. 479-481. Mir Press, Moscow (2005).
3. Birgé, L., P. Massart. From model selection to adaptive estimation, in D. Pollard(ed), Festschrift for L. Le Cam, pp. 55–88, Springer (1997).
4. Lehmann, E.L.: Testing Statistical Hypotheses. P. 24. Nauka Press, Moscow (1979).

## **Автоматическое обнаружение дефектов и коррозии нефтяных скважин по данным магнитно- импульсного дефектоскопа**

Рита Гайбадуллина, Булат Загидуллин, Владимир Бочкарев

Казанский (Приволжский) Федеральный Университет  
{rita.gaibadullina,bulatz}@gmail.com, vbochkarev@mail.ru

**Аннотация.** Магнитно-импульсная дефектоскопия предназначена для выявления различных дефектов и интервалов коррозии. Высокочувствительные датчики, представляющие собой приёмно-возбуждающие катушки, позволяют анализировать отклик от окружающей среды в широком диапазоне времен. В настоящее время определение зон коррозии осуществляется интерпретатором, т.е. носит субъективный характер. Более того, анализ 2.5–3 км скважины (около 300 трубок НКТ и колонны) — это трудоёмкий процесс, в ходе которого часть дефектов может быть пропущена. Для исключения такого рода ошибок необходимо автоматизировать процесс поиска интервалов коррозии. В работе предложен алгоритм автоматического распознавания дефектов, позволяющий разделить типичные и нетипичные отклики. Так же рассмотрено применение пороговой вейвлет-обработки для подавления шумов и предварительной подготовки экспериментальных данных к дальнейшей обработке.

**Ключевые слова:** магнитно – импульсная дефектоскопия, вейвлет-фильтрация, критерий максимального правдоподобия.