METHODOLOGY USING INVERSE METHODS FOR PIT CHARACTERIZATION IN MULTILAYER STRUCTURES

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Abstract. This paper presents a methodology incorporating ultrasonic and eddy current data and NDE models to characterize pits in first and second layers. Approaches such as equivalent pit dimensions, approximate probe models, and iterative inversion schemes were designed to improve the reliability and speed of inverse methods for second layer pit characterization. A novel clutter removal algorithm was developed to compensate for coherent background noise. Validation was achieved using artificial and real pitting corrosion samples.

Keywords: clutter removal, eddy current, inverse methods, corrosion pits, ultrasonics
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INTRODUCTION

Given the material properties of typical aircraft structures and environmental conditions experienced over a service life, corrosion in aircraft structures is a major issue. For the United States Air Force alone, the total annual cost for corrosion management is on the order of a billion dollars. Avoidance of even a small portion of this annual expenditure would result in significant savings. To improve the management of corrosion, limits of existing inspection tools must be addressed. In particular, the ability to characterize the micro-topography of corrosion that forms fatigue and stress corrosion cracking is critical [1]. With this capability, repairs could be better directed to corrosion damage that only exceeds defect criteria with minimal aircraft disassembly. In support of this goal, this work explores the problem of the characterizing the surface topology of corrosion at faying surfaces in multi-layered aircraft structures with the focus on quantifying the size of corrosion pits in both first and second layers.

Although many corrosion techniques for aircraft structures only use a single NDE method such as eddy current, improvements may be achieved through the use of measurement data from multiple methods. Research has investigated data fusion of ultrasonic and eddy current (EC) methods [2] and conventional and pulsed eddy current techniques [3]. In particular, ultrasonic and eddy current methods are quite complementary for multilayer corrosion problems, where ultrasonic methods provide excellent resolution of corrosion in the first layer, while eddy current measurements are sensitive to the presence of corrosion in both the first and second layers. The proposed approach in this paper uses ultrasonic data to characterize the first layer corrosion and thus simplify the second layer characterization problem using eddy current.

To quantitatively evaluate the size of pits in the second layer, inverse methods will be explored. Significant research into inverse methods for flaw characterization using eddy current data has been performed and can be classified as either model-based or signal processing-based approaches [4-5]. To date, most efforts have primarily addressed the sizing of surface breaking cracks [5-7], with little work on the problem of sizing corrosion pits [8]. Model-based inverse methods have been investigated for flaw characterization; however, the ill-posed character of such problems, long model solution and inversion times, and the presence of background noise can hinder practical application. This paper presents a methodology using model-based inverse methods for second layer pit characterization with the focus on addressing these key issues. Experimental validation of the methodology is also presented using artificial and real pitting corrosion samples.

OVERVIEW OF APPROACH

A diagram is shown in Figure 1 of the general process incorporating inverse methods for processing measurement data for estimation of pit dimensions. To improve the reliability and speed of classifiers using inverse methods, the design of each step in the process must be considered to (1) reduce sensitivity to noise, (2) best address the inherently ill-posed character of inverse methods for parameter estimation, and (3) reduce overall analysis time. In particular, a pragmatic approach is presented concerning the 'fusion' of ultrasonic and eddy current data, where ultrasonic measurements are used to accurately characterize first layer corrosion topology and thus minimize the number of unknowns in the second layer eddy current inversion problem. This approach contrasts with traditional data fusion where pixel-by-pixel fusion of measurement data is used. In reality, subsurface features such as pits are spread across image data and are dependent upon probe parameters. Thus, models in conjunction with inverse methods are needed to best extract features associated with the dimensions of the pit spread across the image data.

Concerning signal processing, a series of steps were used to automate the extraction of pit features from the 2D raster scan data. To process and identify the location of pits in the first layer in ultrasonic data, the following steps were used: backlash compensation, data normalization, median filtering, adaptive thresholding, image segmentation and quantitative evaluation of local feature for pit identification using time-of-flight data. To pre-process the eddy current data, the following steps were used: backlash compensation,

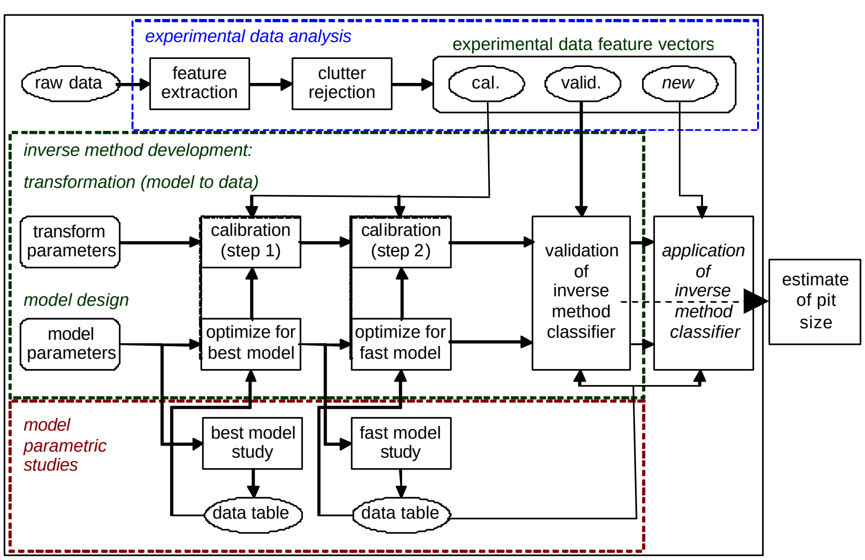

FIGURE 1. Inverse method process diagram.

edge of scan noise removal, image filtering, and locating of pit centers using correlation methods. Both 1D line and 2D circumferential extraction algorithms were implemented to acquire the data vectors for model comparison. Lastly, a novel background clutter removal algorithm was developed and will be discussed in the next section.

Several strategies were also used to improve the reliability concerning NDE models and model calibration process. VIC-3D®, based on the volume integral method, was used as the model for the inverse method [8]. Volume integral methods are inherently efficient in solution time since they only require discretization of the flaw region of a multilayer structure. Look-up tables were also generated *a priori* for classes of inversion problems of interest to eliminate the need for model calls during the inversion process. Interpolation using cubic splines was found to provide an accurate solution between exact model points in the look-up tables. A calibration-based approach was used to efficiently equate voltage measurement data from scanning systems and simulated impedance calculations [9]. Specifically, equivalent pit dimensions were applied to represent complex pit geometries as cylindrical voids, maintaining equal volume and centroid location properties and thus reducing the number of unknowns to solve to only pit diameter and height, thus simplifying the inversion problem. 'Fast' probe models can also replace 'ideal' probe models when properly included in the calibration process. Future work will investigate conical and semi-ellipsoid equivalent pit models that better represent profiles of real pits.

New approaches were also explored concerning the inversion process. In particular, distinguishing the changes in the eddy current response with pit diameter and pit height can be challenging since both parameters impact the overall magnitude of the response. Improving the reliability of inversion schemes can help achieve this goal. Exhaustive searches over ranges of initial conditions were found to be successful in avoiding local minima in the optimization process, while also indicating the most likely solution. An iterative inversion scheme was also developed to address noise in the data to improve the reliability of the inversion process. This method will be discussed in an upcoming section.

CLUTTER REMOVAL ALGORITHM

Model-based inverse methods are a promising approach to improve the characterization of flaws such as fatigue cracks and pitting corrosion. However, the presence of background clutter and noise in eddy current measurements can hinder the performance of inverse methods. Such sources for clutter and noise are often due to probe lift-off variation, local changes in material properties, sensitivity to sub-surface structures, thermal variation of measurement components, and electrical noise. Probe lift-off alone has several potential sources of variation: the alignment of scanning hardware, probe-sample contact conditions, the presence of obstructions such as button-head fasteners and sample surface conditions.

A general concept of clutter removal can be expressed by the following steps. First, an initial assessment is required to evaluate scan regions where the eddy current response is predominantly associated with background clutter with respect to a potential flaw signal. Second, background region variations in the eddy current measurement must be quantitatively evaluated as a function of probe position. Third, extrapolation of the background clutter fit to the flaw region of primary interest is required. Lastly, this relation is then applied to the experimental data, across both background and flaw regions, in order to compensate for the background clutter in the flaw region(s) of most interest.

Previously, the task of clutter removal was performed through manual interpretation and selection of the background clutter regions. Ideally, to make clutter removal a practical tool for in-field NDE applications, there is a need to develop an automated algorithm. A novel clutter removal algorithm is proposed that automates the procedure through assessment of background regions using a model-based evaluation approach. In addition, a higher-order polynomial fit incorporating nonlinear least squares estimation (NLSE) is used to improve the match with the background clutter for improved accuracy in removal. This new approach is presented for application to improve experimental characterization of corrosion pit dimensions.

For this study, linear scans (line segments of 2D raster scan data) will be considered for the problem of eddy current NDE for corrosion pit characterization. To find and center the flaw regions of interest in the experimental data vectors, correlation methods are used. After the flaw data has been centered and transformed for comparison with simulated data, clutter removal can be applied. The proposed clutter rejection algorithm begins with an assessment of the model data. A series of N simulated impedance data vectors consisting of M probe positions are defined as $\boldsymbol{Z_{k,i}}(x_j)$ where $R_i(x_j)$ is the resistance component and $X_i(x_j)$ is the reactance component, representing the i^{th} model data set and j^{th} probe position. To evaluate background regions of interest in the experimental data, the model data is evaluated for regions of scans where the response is invariant to changes in flaw parameters. Figure 2(a) shows a series of simulated data vectors for the reactance component of eddy current impedance measurements for varying pit dimension. It is desired to have model data with pertinent flaw parameters ranging over all expected levels in application. A model-based variation measure, which is used to estimate regions of invariance, is given by:

$$G_k(x_j) = 1 - \frac{s_k(x_j)}{\max(s_k)}, \tag{1}$$

where:

$$s_k(x_j) = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left[Z_{k,i}(x_j) - \overline{Z}_k(x_j)\right]^2}, \tag{2}$$

and k = 1 is associated with $Z_1(x) = R(x)$, and k=2 is associated with $Z_2(x) = X(x)$. Thus, for scan regions with invariance to flaw size, G_k approaches 1, and for locations with greatest variation to flaw size, G_k approaches 0. Figure 2(b) shows an example of the model-based variation measure for the model data show in Figure 2(a). For practical implementation, a threshold function, $G'(x_j)$, can be defined using a minimum variation criteria, g, resulting in regions associated with the background (equal to 1) and flaw (equal to 0). Figure 2(c) displays the threshold function, $G'(x_j)$, defining a select scan region for background clutter fit based on a minimum variation criteria of g = 0.995.

Using the result of the model-based background region assessment, a fit of the background clutter can now be performed. To properly represent the background clutter found in experimental data, a 3rd order polynomial representation,

$$f_{cr}(x) = a_3 x^3 + a_2 x^2 + a_1 x + a_0, \tag{3}$$

was used. The coefficients of the polynomial were evaluated in a least-squares sense with the experimental data fit over the background data point regions. This function can then be applied to the experimental data to subtract the estimated error due to background clutter. Matlab was used for implementation of the automated clutter removal algorithm.

Figure 3 presents a plot of the resistance component at f =1.3 kHz for the transformed experimental data ($\exp_o$) for the case of a subsurface artificial pit (0.062" diameter, 0.062" height) on the back side of the first layer for a two layer stack-up of aluminum panels of 0.125" in thickness. Also, Figure 3 displays the curve, $f_{cr}(x)$, representing a polynomial fit to background clutter and the resulting experimental data with clutter removal (exp_{cr}). Clearly, the application of the automated clutter removal algorithm was found to be beneficial in eliminating the severe background variance across both the background and flaw regions.

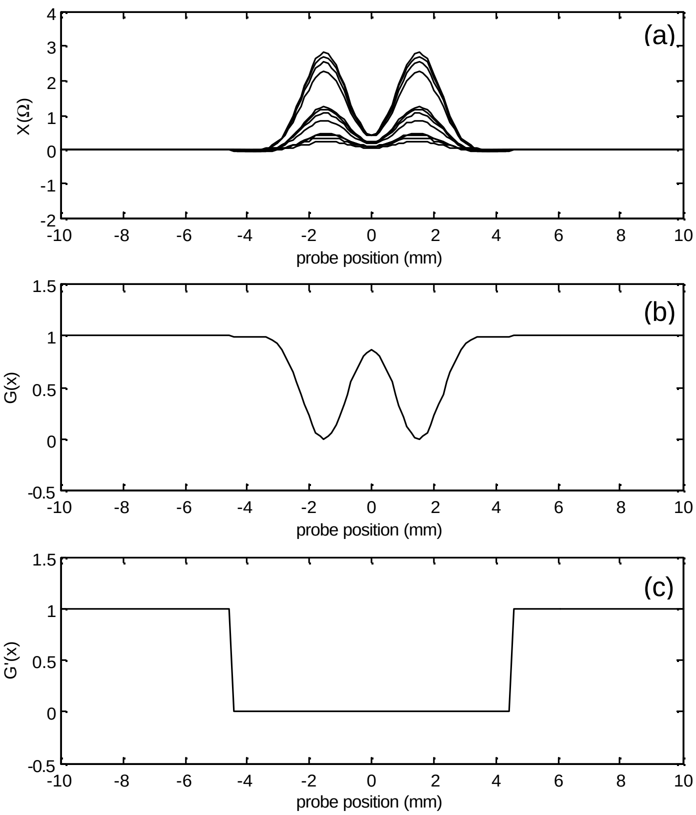

FIGURE 2. Plots of (a) simulated data for the reactance component of EC impedance measurements for varying pit dimension, (b) a model-based variation measure of the reactance components as a function of position, and (c) a threshold function defining a select scan region for background clutter fit.

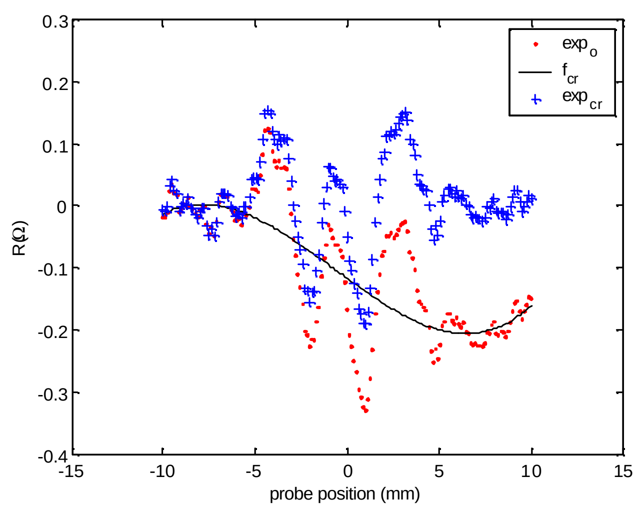

FIGURE 3. Plots presenting experimental data (exp_o), a curve representing a polynomial fit to background clutter, and resulting experimental data with clutter removal (exp_{cr}) for resistance component at f=1.3 kHz.

ITERATIVE INVERSION SCHEME

In addition to coherent background noise, greater measurement noise in one of the two measurement components can also hinder the performance of model-based inverse methods. In experimental data acquired for this program, the transformed resistance component was found to be more susceptible to noise than the reactance component. To address this problem, a novel iterative approach was developed to smooth the noisier measurement component using model-generated results. The iterative inversion scheme shown in Figure 4 uses the model-generated results from the current inversion step to replace the noisy resistance data and repeats the inversion process with the original reactance data and new resistance data. Figure 5 presents an example of the resistance and reactance component for each iteration as the height and diameter of a second layer pit is estimated. For the resistance component, the noise in the scan is eliminated through the iterative process. This approach is viewed as an improvement over discarding the noisier component, since the overall magnitude and profile of the resistance component provide important features to achieve an accurate inversion of both pit height and diameter.

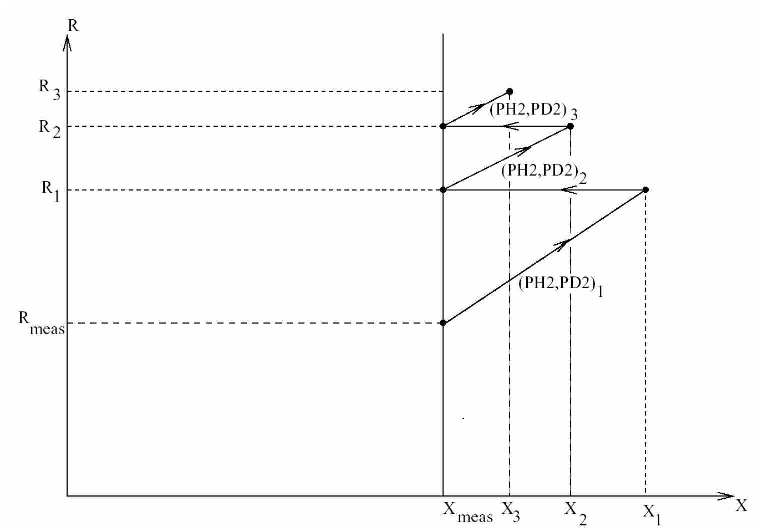

FIGURE 4. Iterative inversion scheme for estimating pit diameter and height refining the measured resistance component using subsequent model-based inversion results.

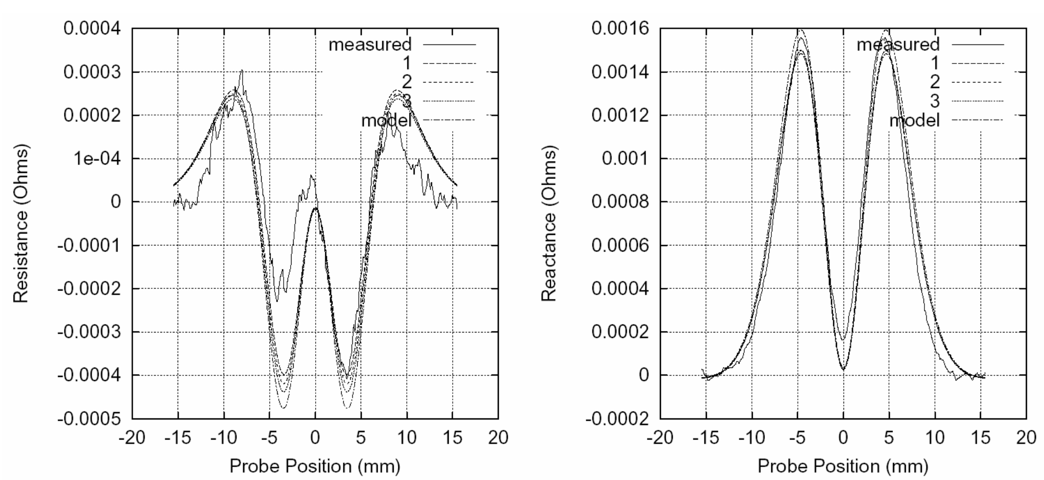

FIGURE 5. Plot of (a) resistance and (b) reactance components of impedance for the original measurement data, iteration results produced by inversion scheme and the exact model result.

RESULTS

Artificial corrosion samples using drilled holes with conical tips to represent real pits were constructed to investigate optimizing the model-based inverse method approach. Simultaneous acquisition of both ultrasonic and eddy current data was performed with the eddy current probe integrated in the Automated Couplant Ejection System (ACES™) head with ultrasonic transducers. Parameters varied in study included: panel thickness (0.040", 0.080", 0.0125"), pit diameters (0.031", 0.062", 0.0125") and heights (0%, 25%, 50% and 75% of panel thickness) in both first and second layers, probe diameter and frequency.

An initial study was performed to evaluate probe and algorithm parameters that impact the accuracy of pit size estimation for pits in the thickest sample set (0.125"). Initially, with the pit diameter tightly constrained, the best results for estimated pit height were determined with an average percent error of only 5.3%. The larger diameter probe (0.057") with the frequency set to 720 Hz was found to provide the best inversion results, as it had the best compromise between depth of penetration and minimization of measurement noise. From the inverse method parametric study, the two algorithm features that were found to be most significant were the use of clutter rejection and a 2D circumferential feature vector. In follow-up studies where the pit diameter was not constrained during the inversion process, the novel inverse method algorithm consisting of multiple runs with varying initial conditions and an iterative method using model data to replace noisier measured data where found to have a greater benefit on inversion results. In general, pit height and diameter were estimated with accuracy between 1 and 20%. However, the ill-posed character of some of the data inversions was found to produce an occasional outlier in the extensive study which resulted in difficultly in making quantitative claims about a particular parameter. An error weighting scheme applied during calibration process is under development and based on recent preliminary data is expected to help address such outliers.

Validation of this methodology has also been made using a sample with real corrosion pitting as shown in Figure 6(a). One of the more significant pitting regions was selected from a set of samples evaluated using laser profilometry [Figure 6(b)]. Ultrasonic time-of-flight data was also acquired to evaluate the pit height and diameter [Figure 6(c)]. The pit height was determined to be 0.020" by laser profilometry and 0.026" using an ultrasonic method. However, there may be some error in the laser profilometry results due to the presence of corrosion by-product. From the image data for each method, an estimate of equivalent pit diameter was also made, varying from 0.040" by laser profilometry and 0.100" using ultrasonic method. It is likely that the pit diameter is closer to the value determined by laser profilometry given beam spread in the ultrasonic measure. Using the proposed methodology for second layer pit characterization using eddy current data from a single frequency of 6.2 kHz [Figure 6(d)], the pit depth was estimated to be 0.029" and the pit diameter was estimated to be 0.058”. These results are in good agreement with the known values for the pit and provide validation of this general approach. In particular, the pairing of the iterative inversion scheme for noise rejection with an exhaustive search varying initial conditions was found to be beneficial for achieving these results.

CONCLUSIONS AND FUTURE WORK

A methodology was presented incorporating ultrasonic and eddy current data and NDE models to characterize pits in first and second layers. The approach highlighted the development of clutter removal algorithms and iterative inversion schemes to best address noise in the measurement data. Good results have been achieved through validation of the methodology with both artificial and real pitting corrosion samples. Future work will

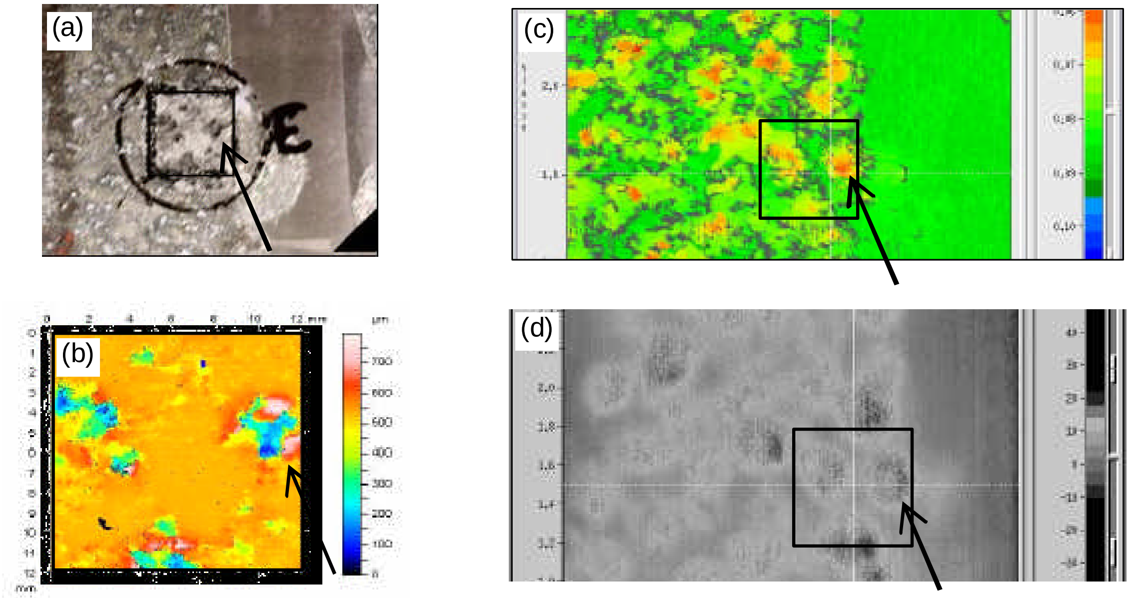

FIGURE 6. Corrosion pit (a) photograph, (b) laser profilometry image, (c) ultrasonic image (pits in far side of single layer), (d) eddy current image (pits in near side of second layer, no corrosion in first).

explore opportunities to improve the quality of measurement data through the use of GMR sensors with improved S/N at low frequencies and novel sensor designs to improve spatial resolution. In addition, the challenges of addressing consistency of estimation results and characterizing multiple closely-spaced pits will also be investigated.

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