QUANTITATIVE RUST-UNDER-PAINT DETECTION UTILIZING NEAR-FIELD MICROWAVE NDE TECHNIQUES

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Abstract: Near-field microwave NDE systems utilizing open-ended rectangular waveguides constitute a competent candidate to detect and evaluate planner rust layers under paint coatings. Basically, the waveguide illuminates the specimen with microwave signals and monitors the reflected waves. Minute variations in the structure reflect in measurable variation in the reflection coefficient at the waveguide aperture. The functional dependence of reflection coefficient on the rust layer physical properties—i.e. thickness and depth—is exploited in the detection scheme. Upon measuring the reflection coefficient, the inverse problem of rust thickness and depth determination should be solved. This problem is ill-posed in nature and requires sophisticated algorithm to be inverted quantitatively. In this paper, we introduce a Maximum-Likelihood algorithm to be applied in conjunction with multi-frequency measurements to solve the inverse problem. As it will be shown, the multi-frequency measurements provide diversity gain over the uncertainties embedded in the system. The practical potential of the proposed algorithm will be demonstrated in real life rust under-paint detection problem. Finally, the performance of the algorithm in noisy environment will be simulated and analyzed. It will be shown that the proposed algorithm provides significant accuracy with high sensitivity in determining the rust layer's thickness and depth.

Introduction: As far as the ultimate purpose of any NDE device is concerned, detection alone is not enough to achieve that purpose. Today, the NDE device is ought to provide the inspector with quantitative assessment of the specimen under inspection [1]. In the rust detection problem, there are two parameters of interest for assessment; the depth and thickness of the rust layer.

Rectangular waveguide-based Near-field microwave NDE systems have shown promising results in detecting corrosion layers under paint coatings [2] [3] [4]. In this paper, a general algorithm to determine the rust layer's depth and thickness from system measurements is presented.

Problem Description: Given a certain specimen to inspect, we need to determine the rust layer's thickness t and depth d. The assessment of both parameters should live up to axial resolution of R. Furthermore, let's assume that we are interested in detecting both parameters in finite ranges. Then, given the required resolution, there are finite sets of possible rust thicknesses and depths of interest for detection. Mathematically, this is described as follows.

$$t \in \{t_1, t_2, ..., t_N\}, \text{ and } d \in \{d_1, d_2, ..., d_M\}$$

$$|t_i - t_j| = R \text{ and } |d_i - d_j| = R, \text{ Where } i \neq j, \quad i = 1,2,...N,\ j = 1,2,...M,$$

N and M are the number of possible thicknesses and depths respectively. In a certain occurrence, the rust thickness would be one of the N possible thicknesses, and by the same token, the depth would be any one of the M depths. In this context, we have MN possible combinations to detect. We can describe the possible combinations by the *detection matrix* given as,

$$D = \begin{bmatrix} t_1 & . & t_N & t_1 & . & t_N \\ d_1 & . & d_1 & d_2 & . & d_M \end{bmatrix}^T$$

The detection matrix contains MN independent combinations (rows). Clearly, the rows of the detection matrix span a space of dimension MN.

1. Forward Model

The forward model describes the relation between the phase of the reflection coefficient and the rust layer's thickness and depth at a certain frequency. It is a non-linear transformation that maps the combination of the rust thickness, rust depth and the frequency of operation to the phase of the reflection coefficient. In mathematical notation this is described as follows.

$$\phi_a = T(t, d, f)$$

where,

ϕ_a is the theoretical phase of the reflection coefficient.

T is the forward non-linear transformation.

t is the rust layer thickness.

d is the rust layer depth.

f is the frequency of operation.

The transformation is supported in the range from –180 to 180 degrees. At given frequency, this transformation can be applied to the detection matrix defined above to yield the *measurement vector* defined as follows.

$$M_f = T(D, f) = \Phi_{af} = \begin{bmatrix} \phi_1 & \phi_2 & . & . & \phi_{MN} \end{bmatrix}_f^T$$

(1)

Since the transformation is non-linear the dimensionality may not be maintained through transformation—this could happen when $\phi_i = \phi_j$, for any $i \neq j$, meaning that we could have the same phase measurement for two different combinations (rows) in the detection matrix.

2. The Inverse Model

In the rust detection problem, the measured phase of the reflection coefficient is used to determine the rust thickness and depth. So, in practice, the forward model is used in an inverted fashion—e.g. given certain phase measurement, what are the rust thickness and depth? In this scenario, the inverse model is also another transformation that is ought to map the measurement vector to the detection matrix. Intuitively, this transformation should be the inverse of the forward transformation defined above. The direct inversion is described as follows.

$$\hat{D}_f = T^{-1}(\Phi_{af}) = \begin{bmatrix} \hat{t}_1 & . & \hat{t}_N & \hat{t}_1 & . & \hat{t}_N \\ \hat{d}_1 & . & \hat{d}_1 & \hat{d}_2 & . & \hat{d}_M \end{bmatrix}_f^T$$

(2)

When $\hat{D}_f = D$, the inverse is said to be unique. It is well known that to have unique inverse of a certain transformation, that transformation should be linear. As we mentioned above, the forward transformation is not linear in the detection matrix. Hence, it is not possible to have a unique inverse transformation simply by inverting the forward model. In other words, the measurement vector does not uniquely characterize the detection matrix. Furthermore, in practice, phase uncertainties usually contaminate the measurement vector. Meaning that, even if the inverse transformation is unique in absence of measurement phase uncertainties, the presence of measurement noise will impair the inverse transformation causing it to falsely map the measurement vector to the detection matrix. In this case, the NDE system will yield false assessment.

Quantitative Inversion Algorithm: In general, the problem of finding a unique inverse transformation that is immune against measurement uncertainties is referred to as the inverse problem. Quantitative solution of the rust detection inverse problem is described next. It is constructive to pin down some definitions first.

- The observation vector: the contaminated phase measurements. In practice phase uncertainties are inevitable in any measurement system.

The depth and thickness are to be determined from a phase measurement given by,

$$\phi_m = \phi_a + \phi_w$$

where,

ϕ_m is the measured phase of the reflection coefficient

ϕ_w is the measurement uncertainty in measuring the phase. This term is modeled as a uniformly distributed random variable with zero mean and variance of $\phi_o^2 / 12$. Where the maximum phase offset ϕ_o is determined from system calibration. Then, the observation vector at a given frequency is,

$$O_f = T(D, f) + \Phi_w = \Phi_{af} + \Phi_w$$

where Φ_w is a phase uncertainty vector of length MN.

- Probability of Accurate Assessment (PAA): the probability of detecting any combination in the detection vector accurately. This reflects the probability of accurately determining any rust thickness and depth in the ranges of interest.

The objective of the inversion algorithm is to find the inverse transformation T^{-1} that operates on the observation vector to yield an estimate of the detection matrix as follows.

$$\widetilde{D}_f = T^{-1}(O_f) = T^{-1}(\Phi_{af} + \Phi_w) = \begin{bmatrix} \hat{t}_1 & . & \hat{t}_N & \hat{t}_1 & . & \hat{t}_N \\ \hat{d}_1 & . & \hat{d}_1 & \hat{d}_2 & . & \hat{d}_M \end{bmatrix}_f^T$$

(3)

In general, the inversion algorithm would be described as optimum if the PAA is maximized.

The inverse problem can be though of as a compound problem of two parts. First, the inverse transformation is not unique due to the non-linearity of the forward model. Second, the presence of the phase measurement uncertainty will deteriorate the detection capability of the system. The proposed inversion algorithm will integrate the solution of each part as shown next.

1. <u>Synthesizing a Unique Inverse Transformation</u>

As it will be shown later, if an inverse transformation guarantees a unique mapping between the measurement vector and detection matrix, then a general optimum detection rule can be derived to maximize the PAA. Thus, we will start by synthesizing a unique transformation T^{-1} given in (2). To this end, we will use one of the most powerful features of near-field microwave NDE; broadband detection. In near-field microwave NDE, comparable phase sensitivities to the rust layer electrical properties can be attained at multiple frequencies. This is true even for frequencies in the same waveguide band. Using this fact, we will synthesize a unique inverse transformation as follows. We need to bear in mind that the problem with the measurement vector defined in (1) is that it does not fully describe the detection matrix. To solve this problem, multiple frequencies will be used to define the same detection matrix.

In a given waveguide band, we will use n different frequencies and evaluate the forward transformation in (1) to form new measurement matrix as follows.

$$\Lambda_n = \left[T(D, f_1) \quad T(D, f_2) \quad . \quad . \quad T(D, f_n)\right]$$

If the columns of Λ span an n-dimension space—i.e. Λ is full rank matrix, then the columns are independent of each other. In our context, each column adds new information about the detection space. To have a unique solution for the inverse problem, each row of the measurement matrix should correspond to one and only one row in the detection matrix. This is described in the following.

$$\grave{D} \xleftarrow[\text{RLT}]{} \rightarrow T(\Lambda_n)$$

where, $\xleftrightarrow[RLT]{}$ is a Row Look-up Table (RLT) transformation that maps the rows of the measurement matrix to the rows in the detection matrix. The criterion upon which the number of frequencies is chosen is that: $Choose$ n such that $\breve{D} = D$.

2. Optimum Detection Rule

Assume that a unique RLT was synthesized in the previous step using n number of frequencies. An n dimensional phase uncertainty will be added to the measurement matrix to form the observation matrix.

$$A_n = \left[T(D, f_1) \quad T(D, f_2) \quad . \quad . \quad T(D, f_n)\right] + \left[\Phi_{w_1} \quad \Phi_{w2} \quad . \quad . \quad \Phi_{wn}\right]$$

In practice, we will be measuring one of the rows in the observation matrix. From our observation, we need to determine which row in the detection matrix corresponds to our observation. Due to the presence of measurement uncertainty, there would be a certain probability that we will decide falsely on the rust thickness and depth. The optimum strategy to reduce this probability, is select the row in the detection matrix, which correspond to the row in the measurement matrix that has the minimum Euclidian distance from the observed row. Basically, this is the Maximum likelihood detection rule that gives the optimum performance for the proposed inversion algorithm.

Practical Rust Under Paint Detection Problem: The proposed inversion algorithm was utilized in practical rust detection problem. The rust thickness was varying from 0 to 300 micrometers and the rust depth was in the range from 50 to 500 micrometers (paint thickness). The required resolution was set to be 50 micrometers in each parameter.

Three frequencies 25, 25.5 and 26 GHz were used to implement the inversion algorithm as described previously. Figures 1, 2, and 3 show the phase of the reflection coefficient as a function of the rust thickness while the paint thickness is varied a parameter at 25, 25.5 and 26 GHz. Immediately apparent is the fact that the relation between the phase and the detection parameters is non-linear. To realize the potential of the inverse problem challenge, a line drawn horizontally at a certain phase value, will cross many parametric depth curves.

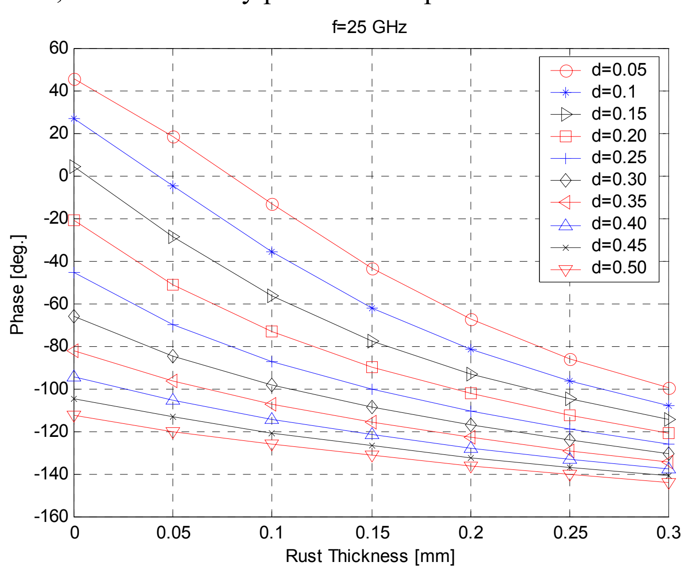

Figure 1: The phase of the reflection coefficient as a function of the rust thickness and depth as a parameter at 25.5 GHz

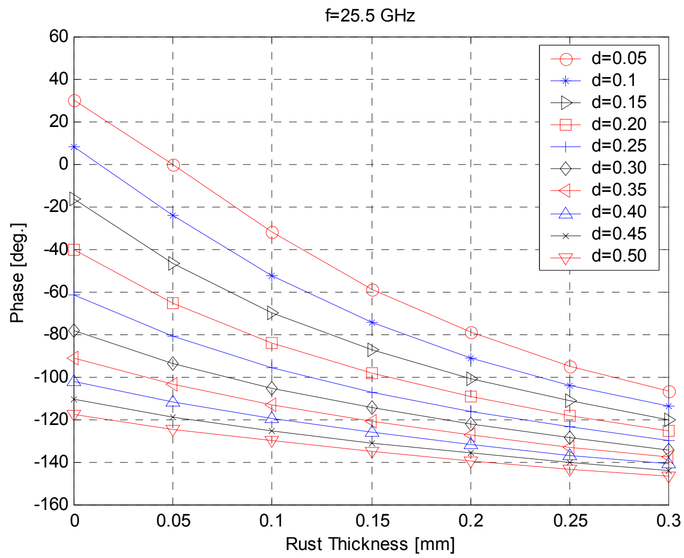

Figure 2: The phase of the reflection coefficient as a function of the rust thickness and depth as a parameter at 25.5 GHz

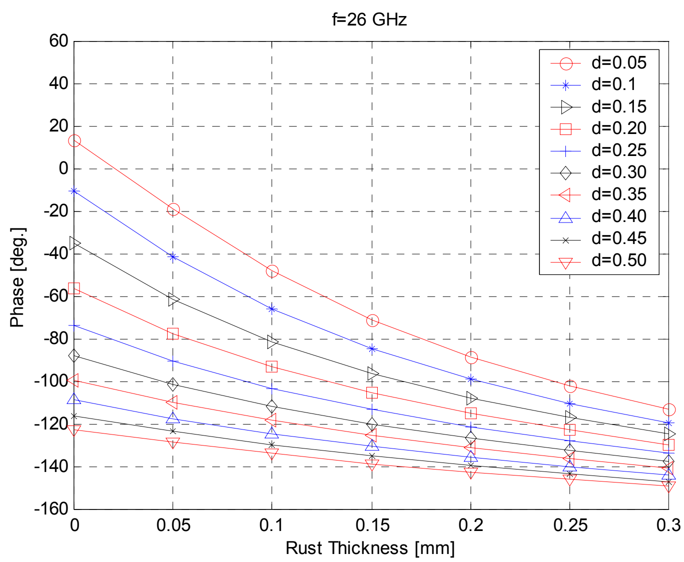

Figure 3: The phase of the reflection coefficient as a function of the rust thickness and depth as a parameter at 26 GHz

Figure 4 shows the probability of accurate assessment (the probability of accurately detecting any rust thickness and depth) as a function of the phase maximum uncertainty offset. As we can see, when the phase offset is zero, we have 100% accurate assessment. This basically suggests that the synthesis of the inverse transformation is perfect. The PAA is maintained above 90% even at high phase offset like 0.5 degree and it decreases to 82% at phase offset of 1 degree. This performance demonstrates the immunity of the proposed algorithm to the measurement uncertainty.

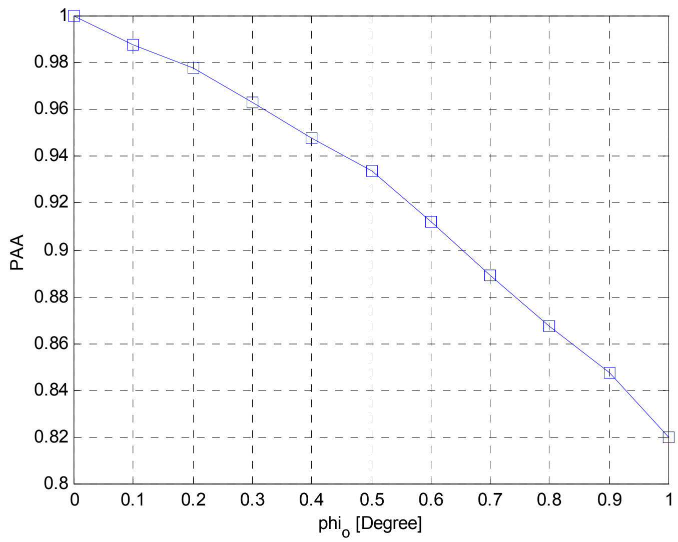

Figure 4: PAA as a function of the maximum phase offset

In the case of false assessment, a good performance measure would be the Mean Squared Error (MSE) in assessment. Figures 5 and 6 show the MSE (mm^2) in determining the rust thickness and depth as a function of the phase offset. It is apparent that the MSE in estimating the rust thickness is kept below 0.005 mm^2 for the whole range of the phase offsets. For the rust depth, the estimation MSE is maintained below 0.008 mm^2 in the same range.

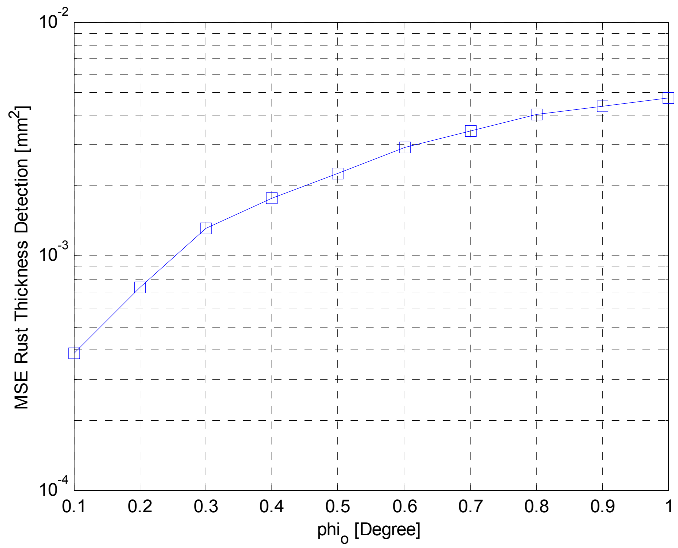

Figure 5: MSE in rust thickness assessment as function of the maximum phase offset

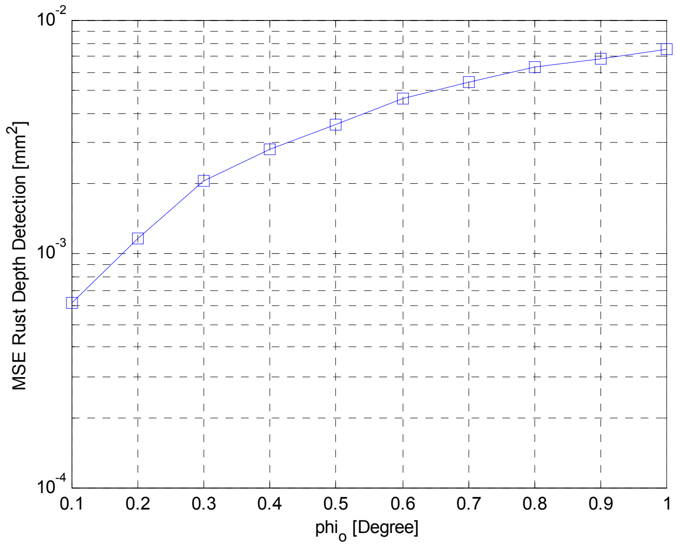

Figure 6: MSE in rust depth assessment as function of the maximum phase offset

To judge the performance of the proposed algorithm quantitatively, figures 4, 5, and 6 should be combined to describe the performance as follows. In a measurement environment where the phase offset is 0.5 degree for example, the probability of accurately determining any rust thickness and depth is 93%, and 7% of the times the inspector will decide mistakenly on another rust thickness and depth (false assessment). Even in the false assessment state, the MSE in the rust thickness would be 0.0012 mm^2. And in the depth the MSE is 0.0035 mm^2. So, the assessment, even if it were a false one, would be very close to the accurate assessment.

Conclusion: This paper was focused on quantitative rust under paint detection problem utilizing microwave NDE techniques. A general inversion algorithm has been developed and applied to a real life scenario. The simulation results highlighted the potential of the proposed algorithm in real life problems. The proposed algorithm if utilized in a detection system, will provide high probability of accurate assessment even when high uncertainty offsets contaminate the measurements. Also, it has been shown that MSE in thickness and depth assessment is small for a practical range of offsets. The MSE performance combined with the PAA suggests that the proposed algorithm effectively facilitates the sought quantitative monitoring of rust layers under paint coatings.

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