

A BAYESIAN LEVEL SET METHOD FOR MICROTTEXTURE REGION CHARACTERIZATION USING EDDY CURRENT DATA

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ABSTRACT

The presence of microtexture regions (MTRs) in engine components made of titanium alloys can have significant impact on the life of those components. While it has been established that eddy current methods are sensitive to MTRs, work has begun only recently to determine the ability of eddy current methods to characterize MTRs. In this work, we propose using Bayesian level set inversion to determine the size and shape of MTRs using eddy current data. The method is applied to a simple test problem: determining the size of an elliptical MTR using the simulated eddy current signal. Extensions to specimens with more realistic geometries are also discussed.

NOMENCLATURE

MTR = microtexture region

ODF = orientation distribution function

1. INTRODUCTION

Microtexture regions (MTRs) are collections of grains and particles with similar crystallographic orientation. They have been primarily reported in the literature for forged metals, specifically titanium alloys. The presence of MTRs can be detrimental to the life of an engine component ([1]); in order to understand the life of components containing MTRs, an NDE technique to detect and characterize MTRs is needed ([2]). The work done up to this point examining the ability of eddy current methods to characterize MTRs has focused on sensitivity studies, using both experimental data and simulations ([2]). The inverse problem of determining MTR characteristics (such as size, shape, and orientation) from eddy current signals has not yet been addressed; our work is an initial attempt to consider this inverse problem.

One of the main challenges of the inverse problem is how best to parametrize the unknown to make the problem feasible. Attempting to estimate the orientation of individual grains is impractical due to both the resolution of the eddy current coil and the sheer number of unknowns. Thus, a reduced order representation of the MTR is needed.

We begin by demonstrating that for a circular absolute eddy current coil, an orientation distribution function (ODF) can be approximated using a single crystallographic orientation. We then apply a Bayesian level set inversion method, (see [3, 4]), to determine the size and shape of MTRs from eddy current data. The method is then used to successfully estimate the size of an elliptical MTR in a simulated specimen. Further applications, including a hierarchical approach to the inversion, will then be discussed.

2. METHODS

The forward model used to both simulate data and solve the inverse problem is the approximate impedance integral (AII) model, see ([5]).

2.1 Level Set Inversion

The level set method assumes that the unknown of interest κ is piecewise constant, that is

$$\kappa(x, y) = \sum_{i=1}^n \kappa_i \mathbf{I}_{D_i},$$

where \mathbf{I}_{D_i} is the indicator function, the constants κ_i are assumed known a priori, the value of n is fixed, and the spatial domain of the unknown is given by $D = \cup_{i=1}^n D_i$. Note that the regions D_i do not overlap. The main goal of the method is to determine the boundaries between regions. In this way, the inverse problem becomes a classification problem.

The unknown of interest κ is found by optimizing a level set function u . The smooth, continuous level set function u is related to κ via a set of thresholds c_1, c_2, \dots, c_{n-1} which determine the membership of each spatial point, that is

$$D_i = \{ (x, y) \mid c_{i-1} < u(x, y) < c_i \}.$$

The inverse problem is to find the value of u which produces a model output closest to the data.

2.2 Bayesian Approach

Within the Bayesian framework, the solution to the inverse problem is given by the posterior distribution of the unknown, that is

$$p_{post}(u | y) \propto p_{likelihood}(y | u)p_{prior}(u),$$

where y is the measured data. The likelihood describes the distribution of the data given a fixed value of the unknown, while the prior conveys information we have about the unknown before taking into account the data.

In this context, the Bayesian approach allows us to incorporate any prior beliefs we have about the spatial properties of the unknown (such as length scale). Furthermore, sampling from the posterior provides a way to quantify the uncertainty in the estimated boundaries.

3. RESULTS AND DISCUSSION

3.1 Single Orientation Results

We first show that ODFs can be approximated using a single crystallographic orientation. A simulated specimen containing an elliptical MTR with a predominantly basal orientation embedded within another region that is non-basal is shown in the IPF map in Figure 1(a). The horizontal component of the corresponding simulated eddy current signal is also plotted in Figure 1(b). Assuming that size and shape of each region were fixed, we estimated a single crystallographic orientation for each region that resulted in an eddy current signal which was closest to the original simulated data. The simulated eddy current signal with these best-fit orientations is shown in Figure 1(c), along with the difference between the two in Figure 1(d). Although there is some error, the signal assuming a single orientation for each region is quite close to the eddy current signal assuming the full ODF for each region.

3.2 Level Set Results

Having established that the ODFs can be approximated using a single orientation, we apply level set inversion to the simulated data shown in Figure 1 with $n = 2$. We assume a Gaussian prior for u , that is

$$u \sim N(0, \Gamma), \quad \Gamma_{ij} = \exp\left(-\frac{(x_i - x_j)^2}{\ell_x^2} - \frac{(y_i - y_j)^2}{\ell_y^2}\right).$$

The length scales ℓ_x and ℓ_y are assumed fixed; the threshold c_1 was determined empirically for this initial demonstration.

The likelihood distribution is also Gaussian,

$$p(z | u) \propto \exp(-\|z_h - f_h(u)\|^2 - \|z_v - f_v(u)\|^2),$$

where z_h and z_v are, respectively, the measured horizontal and vertical components of the impedance, and $f(u)$ is the forward model. The original simulated sample was generated assuming a 10 micron grid; to avoid the inverse crime and reduce the dimensionality of the inverse problem, we assume a 100 micron grid step size for the inversion.

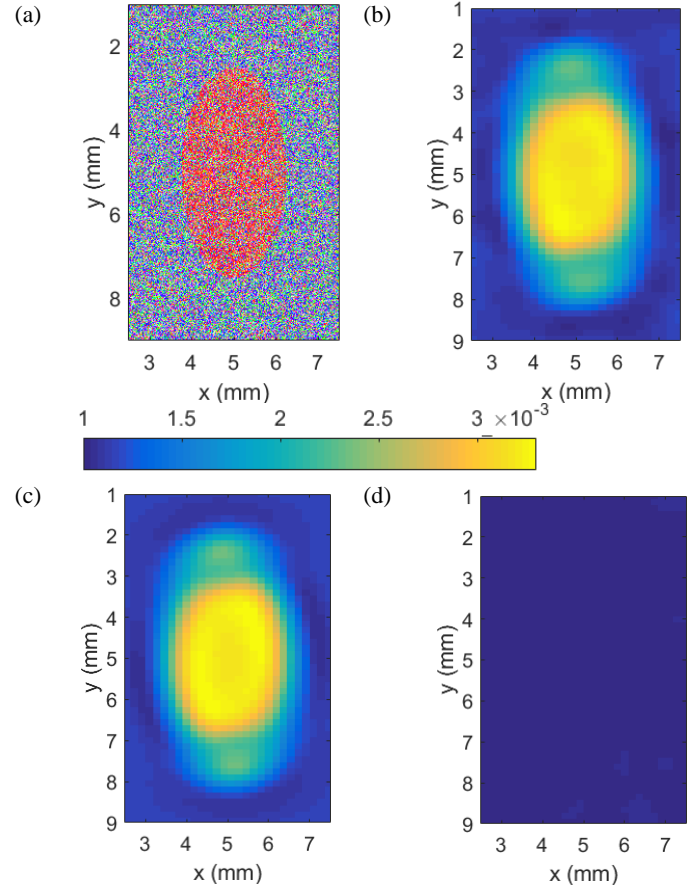


FIGURE 1: Results of representing ODFs using single orientations. (a) The IPF map of the simulated specimen. (b) The horizontal component of the simulated eddy current signal assuming the full microstructure (c) The simulated eddy current signal assuming a single crystallographic orientation for each region. (d) The difference between the two.

A sample from the posterior was generated using a sequential Monte Carlo method, specifically the sampling importance resampling (SIR) algorithm (see [6]). We propagated a total of $N = 50,000$ particles through 50 iterations of the algorithm. We computed the mean of this sample and then applied the threshold to determine the membership of each spatial point. The mean after applying the threshold is shown in Figure 2.

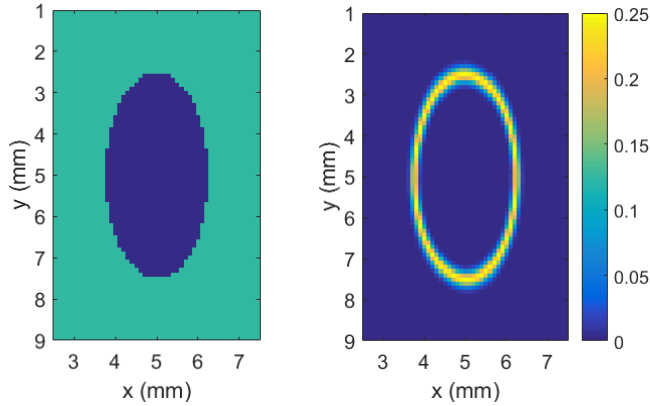


FIGURE 2: The mean of the sample after applying the threshold is shown on the left; the variance of the region assignments is shown on the right.

The resulting mean shows an elliptical region in the same location and with the same size as the elliptical MTR in the original specimen. (The size of the true elliptical region is 9.8175 mm^2 ; the estimated size is 9.75 mm^2 .) Note that the inverse problem essentially amounts to determining which of two potential orientations should be assigned at each spatial point in order to match the original data. In our results, the orientation assigned to the points in the elliptical region is the orientation associated with the elliptical MTR in the original specimen.

In addition, we applied the threshold to each of the N particles and computed the variance of the assigned membership at each spatial point. (We note that the assigned membership is simply an integer – in this case either 1 or 2.) This result is also shown in Figure 2.

Lower variance indicates a higher confidence in the estimated mean, since it implies that the assigned membership is the same in the majority of the sample particles. The variance is, not surprisingly, highest at the border of the elliptical MTR. However, the region with high variability surrounding the border is relatively narrow, indicating that the method is fairly confident in the estimate of the size of the ellipse.

Although this is a simplified problem, it demonstrates the feasibility of the level set method for MTR characterization.

3.3 Extensions to More than Two Regions

This initial demonstration of the technique was limited to a case with one MTR. As indicated in ([3, 4]), one issue with the current formulation is that it restricts what types of regions can be adjacent to one another; it also prohibits any geometries where three different types of regions meet. To remove these restrictions, we instead will consider vector-valued level set functions, as suggested in ([4]).

For the initial results we assumed that the single crystallographic orientations that represented each ODF were known and fixed; moreover, we also assumed that the threshold for the inversion and length scales for the prior were fixed. A hierarchical approach to simultaneously estimate the length scales and threshold was introduced in ([3]); future work will

apply this method to MTR data. In addition, we will consider estimating the orientations of each region along with the unknown using a similar approach.

Another open question is what information can be learned about the orientation of an MTR from eddy current data; for instance, although an MTR can be represented using a single orientation, it is unclear how this single orientation is related to the ODF of that MTR. Further study will be needed to understand the connection between the two.

4. CONCLUSIONS

We have developed a level set method that is able to determine the size and shape of an MTR using eddy current data in a simulated specimen. Further work is needed to extend the technique to realistic geometries, as well as to real data.

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