Considerations for the Identification of Elasto-Plastic Material Model Parameters

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ABSTRACT
Accurate computer modeling and simulation is necessary for the design of advanced engineered components. The reliability of these computer models depends on the accuracy of the user-defined material model parameters and their ability to capture the physical phenomena in the simulation. However, the experimental data used to calibrate these models are often prone to biases due to systematic limitations of the measurement technique, or experimental anomalies. Therefore, these biases must be considered when attempting to inversely identify material properties from an experiment. This work focuses on reducing the bias in the final-calibrated material model by careful intervention in the inversion process.

KEYWORDS: Digital Image Correlation, Finite Element Model Updating, Virtual Strain Gage, Material Model Calibration, Levelling

INTRODUCTION

Full-field measurement techniques, such as digital image correlation (DIC), provide large amounts of motion data from a single experiment. This allows a more robust comparison to a numerical model than point measurements from more conventional metrological devices such as strain gages. The DIC data can be combined with inverse identification techniques to extract model parameters describing the material behavior. The two popular inverse techniques include the virtual fields method (VFM) [1], which has proven useful when testing thin samples, finite element model updating (FEMU) [2], which is slower but requires less information (e.g. volumetric data) or fewer assumptions (e.g. plane stress) and as such will be the focus of this work.

DIC measurements used in the identification often suffer spatial resolution errors due to underfitting of the shape functions to the underlying motion [3]. Additionally, errors due to the experimental noise [4] and the underlying image gradients [5-6] can be detrimental to measurement accuracy. It was shown in [7] that the influence of these errors in the finite element (FE) model validation could be mitigated by filtering the FE output through a DIC simulator, a process termed "DIC-levelling".

BACKGROUND

Since the implementation of DIC-levelling, it has been found that for the purposes of material model parameter identification, errors due to the experimental noise and image gradients had a small effect on identification accuracy [8]. Thus, accurate identifications could be performed by "direct-levelling" the FE data through the same low pass filters as the DIC data without the generation of synthetic images as the authors did in [2]. However, these same authors concluded that more intervention such as from the full DIC-levelling process might be needed for more complicated material models where the effect of second order error terms such as image noise may be more detrimental.

work seeks to highlight further considerations in the FEMU identification beyond levelling of the FE data including but not limited to: rectifying discrepancies between the ideal boundary conditions and those realized in the experiment due to the inherent design and limitations of the experimental configuration, model form error due to plane stress assumptions often used to reduce computation time, and model form error due to the underfitting of the material model to the underlying motion by assumptions such as material symmetry.

ANALYSIS

In this work, a 304 stainless steel hourglass specimen was machined from the bulk sheet transverse to the rolling direction. Due to the radii in the geometry used (shown in Fig. 1), this 1-mm thick specimen produced heterogeneous deformation that could be measured in the DIC data. The material was, for the purpose of this initial analysis, assumed to be isotropic during elastic and inelastic deformation. The von Mises yield criterion was used with hardening defined by the power law:

$$\sigma_y = \sigma_0 + B(\bar{\varepsilon}^p)^n. \tag{1}$$

Equation 1 is the quasi-static hardening term in the Johnson-Cook [9] hardening law. The flow stress, σ_y, is dictated by the initial yield strength, σ_0, hardening modulus B, and hardening exponent n for the value of the equivalent plastic strain $\bar{\varepsilon}^p$.

The specimen was fixtured in a Psylotech μTS 1.6kN load frame and images were captured with an image scale of 122.9 pixel/mm using Correlated Solutions' stereo microscope DIC system. Loading was performed with a cross-head speed of 0.005 mm/s and images were acquired at 1 Hz. DIC was performed using a subset size of 31 pixels × 31 pixels, a step size of 5 pixels and a virtual strain gage (VSG) size of 1.0 mm to calculate the Green-Lagrange strain tensor.

The authors in [10] suggested that due to uneven tightening of the load frame grips, assuming uniform loading could result in error in the FE model to capture the motion in the experiment. To correct for this, they measured the motion near the boundary of their DIC measurements for both sides of the specimen and applied the DIC displacements as boundary conditions in their FE model. The schematic in Fig. 2 shows a similar process that was implemented in this work but for a single side of the specimen. The left full-field plot shows the *V*-displacement at a single time step in the experiment as well as two red dashed lines where we measured the displacement. The middle plots show the measured motion (red dots) from the line scans. A quadratic polynomial (blue line) was fit to smooth the data into a continuous function which could be more readily applied to the FE model for both the *U* (not shown) and *V*-displacements. The plot on the right shows the nodes of our ABAQUS FE mesh consisting of 5,202 CPS4 elements. The displacement defined from the polynomial fit in the previous panel was applied to the nodes outlined by the red circles.

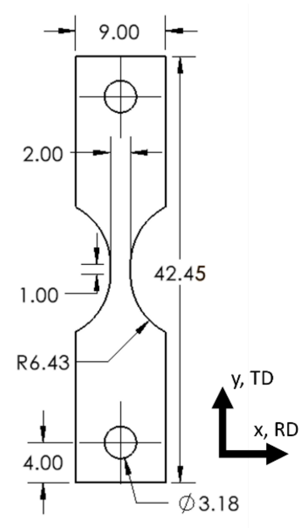

Fig. 1 The dimensions in mm of the 304 stainless steel hourglass specimen for our identification.

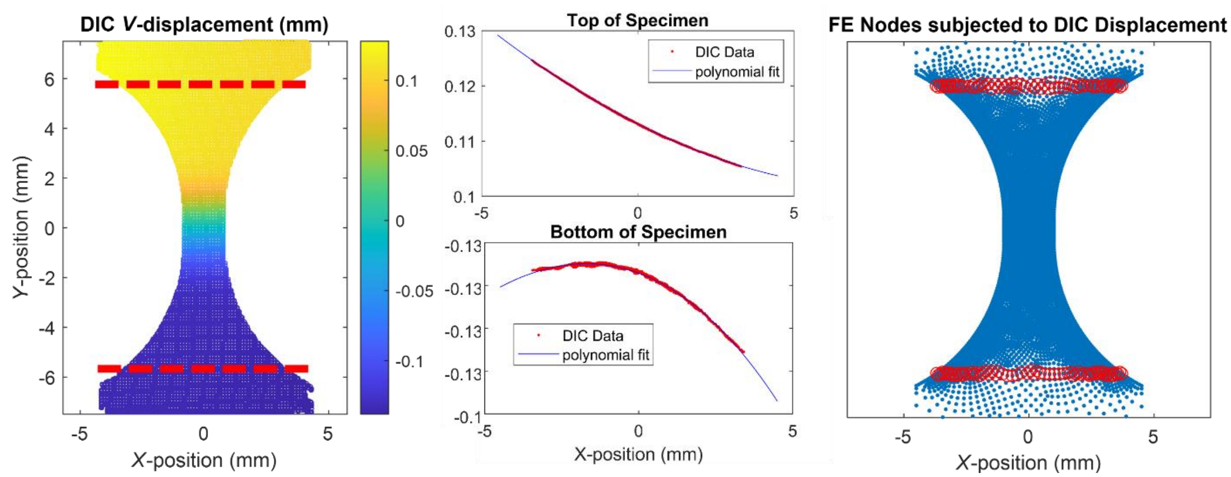

Fig. 2 Schematic showing the process of applying the DIC-measured motion as boundary conditions to the FE model.

FEMU identification was performed by minimizing the cost function shown in Equation 2 with respect to the material model parameter vector $\boldsymbol{\rho}$ for a single load step when the resultant force was 922 N. The cost function was the weighted sum of squared differences of the Green-Lagrange strains E, and the resultant force due to the displacement loading for both the experimentally (exp) measured and numerically computed (FEA) quantities.

$$\chi^2(\boldsymbol{\rho}) = \sum_{\Omega_{exp}} \left[E_{exp} - E_{FEA}(\boldsymbol{\rho})\right]^2 + \frac{1}{\gamma_f^2}\left(F_{exp} - F_{FEA}(\boldsymbol{\rho})\right)^2. \tag{2}$$

The contribution due to the force terms was normalized by a weighting coefficient, γ_f^2, to balance the contribution from the strain and forces. The FEA strain was calculated using the ABAQUS displacements following the direct-levelling method described in [8]. The initial guess for the FEMU routine was 339 MPa for σ_0, 1,070 MPa for B, and 0.645 for n, which were based on a previous tensile test performed in [8].
The FEMU identification concluded after 10 iterations where the norm of the unity-scaled parameter update vector was less than the threshold limit of 0.0001. The parameters were found to be σ_0 = 315 MPa, B = 1,301 MPa, and n = 0.704.

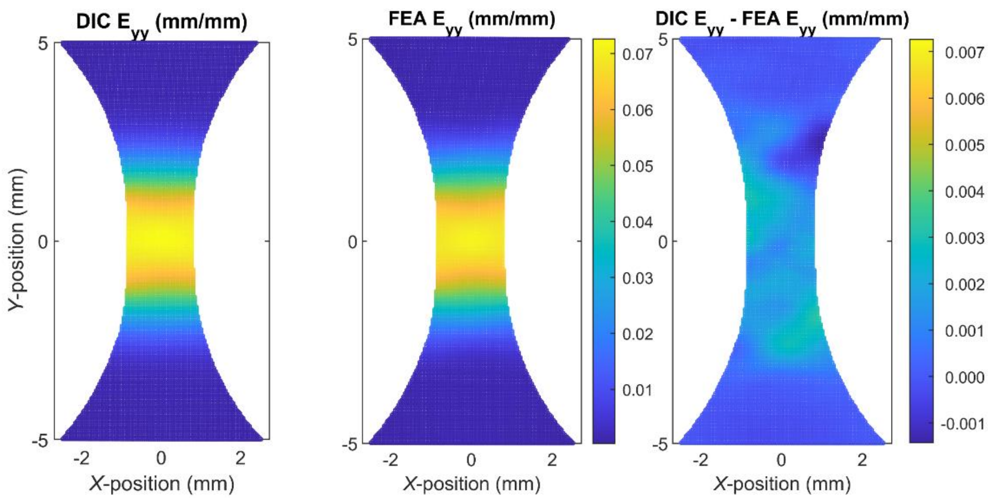

Fig. 3 Results of the fit of the FEA-computed strain to that measured experimentally after material model parameter identification from FEMU.

The plots in Fig. 3 show good agreement between the DIC measured strains and those computed from the forward solve of the model with the identified parameters. The accuracy for this identification is only shown for a specific orientation, geometry, load increment, and surface measurement. Thus the material model parameters of this identification should not be generally applied to a model under different settings. This is a point that will be discussed further in the future work.

CONCLUSION

Thus far, we have fit the deformation and load of a plane-stress FE model to the experimentally measured counterpart in an attempt to identify the material model parameters to describe the material hardening. As a first step, discrepancies between the spatial resolution and loading of our specimen were rectified by direct-levelling the FEA data to the DIC data and applying the experimentally measured displacements at regions near the edge of the DIC region of interest as boundary conditions for the FE model. Further considerations must be implemented from here to achieve a model that more closely resembles the physics of our material, for example using constitutive equations that describe the anisotropy of the material and assessing the error due to the assumption of plane stress. In a following work, a separate validation experiment will be performed to assess the model form error for this set of constitutive equations and other more anisotropic models with and without the assumption of plane. The combination of identification interventions to calibrate several classes of constitutive model in addition to separate validation studies should result in a more accurate identification that can be generally applied to other FE models.

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