A New Approach Based on Neural Network for a 3d Reconstruction of the Dome of a Bulge Tested Specimen

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Abstract

A three-dimensional reconstruction of the dome formed by a thin hyperelastic specimen during a creep bulge test was carried out through two different techniques: stereoscopic reconstruction based on epipolar geometry and Digital Image Correlation. A suitable experimental device, provided with a sliding crossbar for acquiring dome images so to detect its strain state, was used for the epipolar geometric reconstruction. In 3D reconstruction based on the Digital Image Correlation, the cameras/sliding crossbar system was replaced by a different optical system. A new approach to exploit the greater accuracy obtained with Digital Image Correlation, using cheaper techniques, was based on the training of a Convolution Neural Network. This training consisted in using a set of points (x, y) of the specimen at different pressure values in order to obtain a heights (z) map of the dome. This approach is aimed to reconstruct the dome providing to the Network thus trained the images from a single camera placed on the vertical axis of the dome apex.

Keywords

Bulge Test, Hyperelastic, Epipolar, 3D-DIC, Neural Network

1. Introduction

Nowadays elastomers are widely used in the automotive and mechanical industries to make tires, hydraulic or pneumatic drive units, hydraulic hoses, anti-vibration mounts, pneumatic and hydraulic shock absorbers.

These materials exhibit large deformations with highly non-linear hyperelastic behavior [1]. The mechanical characterization, aimed at defining the hyperelastic constants describing the behavior of elastomers, requires the use of different types of tests. Among these, the bulge test is a consolidated technique for the study of membranes subjected to an equibiaxial tension state [2, 3, 4]; this test can also avoid the damage that can occur on the edges when the specimen is stressed during other types of tests.

The bulge test consists in fixing a thin specimen between two circular flanges with holes in the center to allow, through the insufflation of fluid inside the test chamber, the inflation and therefore the deformation of the material. During inflation, the characteristic parameters of the test are monitored: pressure and displacements. The data thus obtained will then be converted into stress and strain values. Some of the authors have already published a mobile crosshead device capable of subjecting a membrane to the bulge test in force control (creep) [5, 6].

In this study, the three-dimensional reconstruction of the dome of a bulge-tested specimen was performed with two different techniques: stereoscopic reconstruction based on epipolar geometry and Digital Image Correlation (DIC) [7, 8]. The data obtained from the latter methodology were used to properly train a convolutional neural network (CNN). The neural network thus trained will be able to reconstruct the dome on the basis of frames from a single camera placed on the vertical axis of the apex dome, while maintaining the level of accuracy achieved with 3D-DIC in the training phase. This involves an obvious saving both temporal and economical.

2. Materials and Methods

The material tested in this study is SBR 20% carbon black-filled that is an artificial rubber widely used for making tires, seals and shoe soles [9, 10, 11]. A set of 10 square specimens (180 mm × 180 mm) were cut from a single sheet of elastomer having a thickness of 3 mm. Each specimen presented a different pattern on each of the two faces (Fig. 1). On the first, useful for the epipolar reconstruction, a grid consisting of five concentric circles (*parallels*) was silk-screened,

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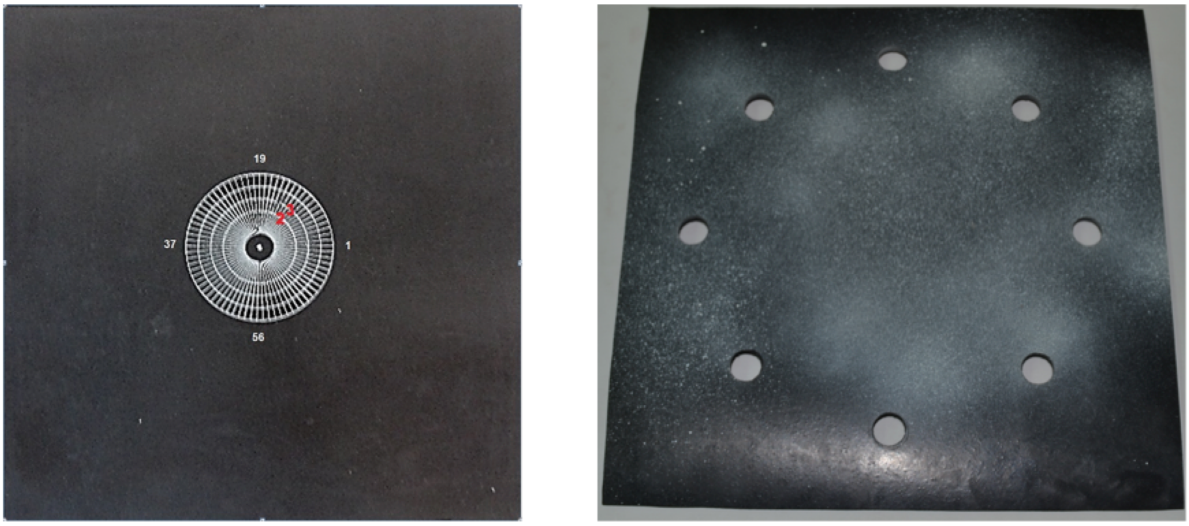

Figure 1: Left: Side for epipolar reconstruction. In white and in red meridians and parallels considered in CNN, respectively. **Right:** Side for DIC reconstruction. In this sample, holes for clamping are already made.

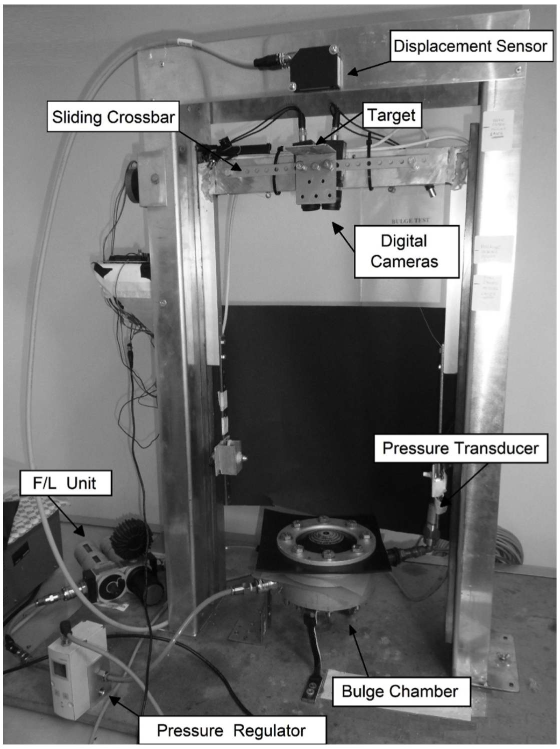

Figure 2: Bulge test setup for epipolar geometric reconstruction (Courtesy of the authors [9]).

a small central circle whose center corresponded to the top of the dome and 73 equidistant rays (*meridians*) radiating from the center. On the second face, on which to carry out the 3D-DIC, a pattern of random

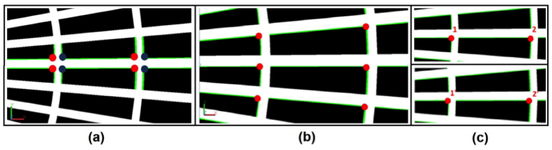

Figure 3: (a) Light transitions: dark to light (red point) and light to dark (blue point). (b) Homothetic markers. (c) Comparison of the distance between two homothetic markers at two successive stress states (Courtesy of the authors [6]).

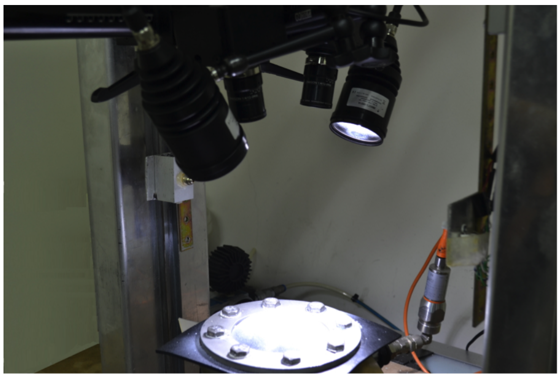

Figure 4: Bulge test setup for 3D-DIC reconstruction.

spots of white paint was airbrushed (with nozzle diameter ϕ = 0.18 mm). In this way, spots obtained had an average diameter ϕ = 0.23 mm and a relative surface A = 0.042 mm^2.

The bulge test technique is based on some restrictive assumptions both on the tested material (isotropy and

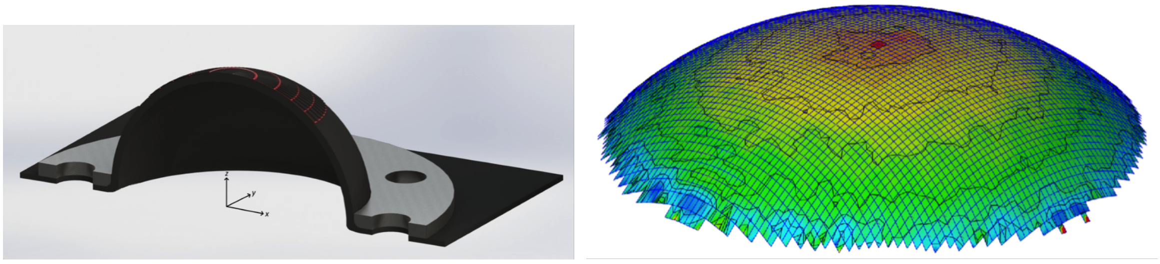

Figure 5: Left: Epipolar geometric reconstruction of the dome (Courtesy of the authors [9]). **Right:** 3D-DIC reconstruction of the dome.

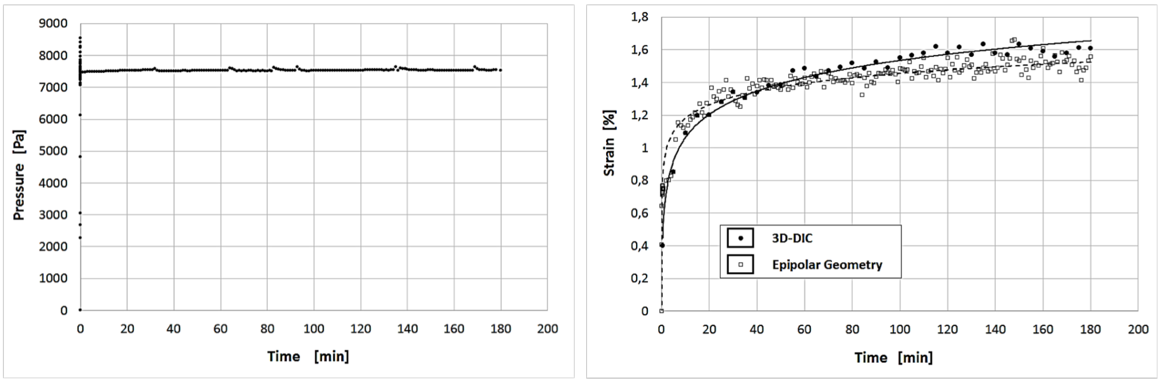

Figure 6: Creep-test diagrams.

incompressibility) and on the geometry of the inflated specimen (hemispherical shape and reduced thickness compared to the radius of curvature). Under these assumptions, the stress state can be considered plane and equibiaxial, allowing the Boyle-Mariotte law, valid for thin-walled tanks, to be applied:

$$\sigma_c = \sigma_a = \frac{p \cdot S}{2 \cdot s} \tag{1}$$

where σ_c and σ_a are, respectively, the circumferential and axial tension, s is the thickness at the apex, R is the radius of curvature of the dome and p is the inflation pressure.

At the apex of the dome each meridian is a main direction and the stress state is equibiaxial. Therefore, on the surface of the dome the main deformations are equal to each other ($\epsilon_1 = \epsilon_2 = \epsilon_{eq}$). From the knowledge of the undeformed length l_0 and the deformed length l_d of a membrane finite element, these deformations are:

$$\epsilon_1 = \epsilon_2 = ln\frac{l_d}{l_0} \tag{2}$$

From the equation of the well-known equivalent deformation of Von Mises, respecting the assumption of incompressibility of the material [12]:

$$\epsilon_3 = ln\frac{s}{s_0} \tag{3}$$

where s_0 is the initial thickness of the specimen.

3. Experimental Setup

The experimental setup (Fig. 2) consists of a bulge chamber, inflated by a compressed air system allowing to accurately adjust the pressure, and of a mobile crossbar to which two cameras are fixed to detect the equibiaxial strain of the specimen.

The mobile crosshead device, controlled by an optical system, moves the fixed focus cameras following the inflation of the specimen. This means that the dimensions of the captured images depend exclusively on the deformation at the dome and not on its approaching to the camera lenses. The measurement of the equibiaxial deformation (ϵ_{eq}), according to the eq. (2), is obtained by comparing the distances between two homothetic markers relative to two successive instants during the creep of the material (Fig. 3). To measure the displacement more accurately 33 samples, at a sample rate of 1 kHz, were acquired for each image.

The acquisition time was equal to 1/30 *s*, corresponding to the camera frame rate. During each acquisition, the average of the 33 values, as a representative value, and the standard deviation of the series were calculated. The resulting synchronization uncertainty was 1/30 *s*, equal to the phase shift of a single frame. Moreover, the displacement signal will be less affected by the electronic noise.

In order to achieve the 3D reconstruction based on DIC, GOM ARAMIS 2M LT optical system replaced the device with cameras/sliding crossbar (Fig. 4).

Figures 5a and 5b show the three-dimensional reconstructions obtained through epipolar geometry and 3D-DIC, respectively. The creep-test was performed by inflating air into the chamber as quickly as possible until reaching a pressure of 75 kPa, keeping it constant for the entire test period (Fig. 6a). This value, much lower than the breaking pressure of the specimen, allowed to fall within the elastic range so that the two faces of the specimen could be tested with the measurement methods adopted. Fig. 6b shows the creep strains measured with the two methods adopted.

4. Description and Training of the Neural Network

The architecture of the CNN is largely used in computer vision problems. The main structure used is the Inverted Bottleneck as residual block that allows having a good performance together with limited impact on the hardware [13].

In this study, a CNN was trained with data extracted from the mesh generated by the 3D-DIC system (Fig. 7).

The CNN was trained in PyTorch [14] through the ADAM optimizer and the Mean Squared Error (MSE) as loss function for 100 epochs with an initial learning rate (l_r) of 0.001 and batch size of 4. The weight decay was set to 10^{-5} and l_r was scaled of 0.1 after 20 and 90 epochs.

To achieve the heights (z) map prediction, the CNN needed 9 coordinate points (x, y) per creep test as input: 8 points from the intersection of meridians 1, 19, 37, 56 and parallels 2 and 3; 1 from the apex of the dome. In addition, the current pressure was required.

5. Results and Conclusion

Fig. 8 shows the dome reconstructed by the CNN neural network reached after a learning time of 100 epochs. The good performance of this network is highlighted

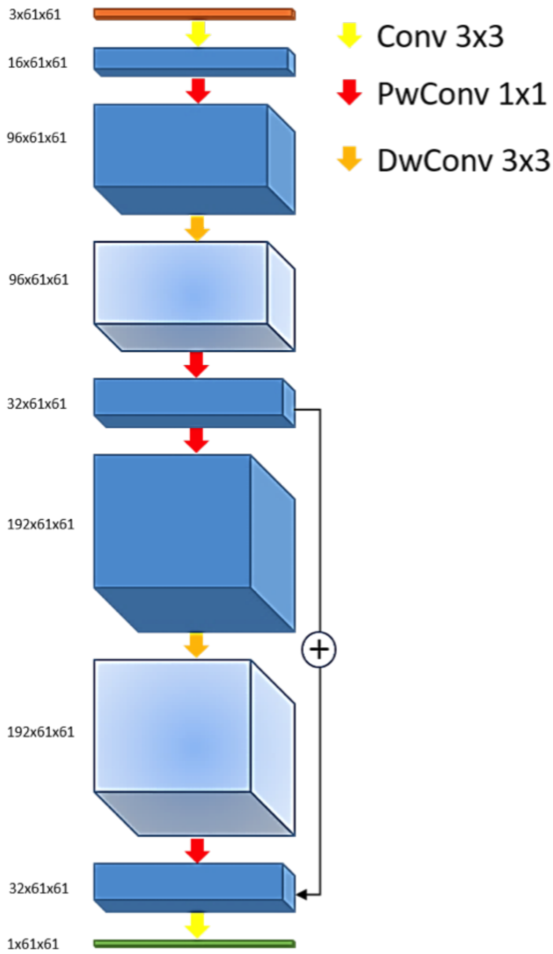

Figure 7: CNN Neural Network.

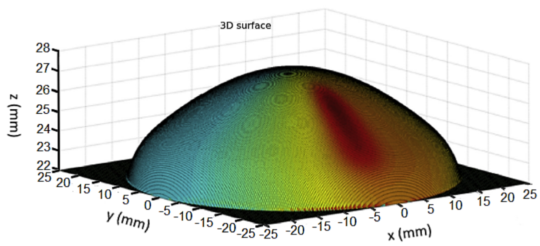

Figure 8: CNN reconstruction of the dome.

by the value of 0.0147 found, over the testing set, for the mean square error among test and train curves.

The application of the CNN neural network has proved useful both from the point of view of time and economic savings. In fact, the reconstruction of the dome can be performed simply based on the frames of a single camera placed on the vertical axis of the dome apex, thus ensuring the same level of accuracy achieved with 3D-DIC in the training phase.

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