Use of Digital Image Correlation and Machine Learning for the Optimal Strain Placement in a Full Scale Composite Tidal Turbine Blade

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Abstract. The testing and health monitoring of large structures represents many challenges, how to get as much information as possible from the specimen under analysis with a limited number of sensors. In this work, we use a data-driven approach using information from a Digital Image Correlation (DIC) system mixed with machine learning algorithms (MLA) to decide the optimal location of single-point strain gauges.

Introduction

Nowadays, technologies such as DIC allow for capturing vast information that reveals the deformation and stresses of small and large structures on almost all their surface. Compared with traditional strain gauges, it offers a huge benefit. Nevertheless, DIC requires specific setup and environmental conditions (i.e., light) that hinder their implementation outside of controlled environments (i.e., laboratories), and then the use of stain gauges is necessary. Still, the optimal number of measurement points and their location remains open. To address this, we used the information from DIC in an MLA to select the points that keep most of the sparsity contained in the stain map revealed by the DIC.

Test Data and Setup

The data was collected at FastBlade, a testing centre that allows for testing large slender structures (2-14 meters) under either static or fatigue loads, as shown in Figure 1. The facility utilises a unique Digital Displacement® Pumps system, which incorporates regenerative pumping and digital displacement hydraulics, enabling accelerated testing (up to 1Hz) with high loads (up to 1MN) [1]. The DIC images were collected and processed using MatchID® [2] software for a clamping test, two static and one fatigue test. The test was performed using three actuators and holding loads for six hours in static and up to 28,000 cycles in fatigue, simulating natural environmental conditions. The DIC setup (Fig 1.) consisted of four cameras working in pairs. Two cameras pointed to the region between the root of the blade and the first actuator, and the other two pointed to the region between the first and the second actuator.

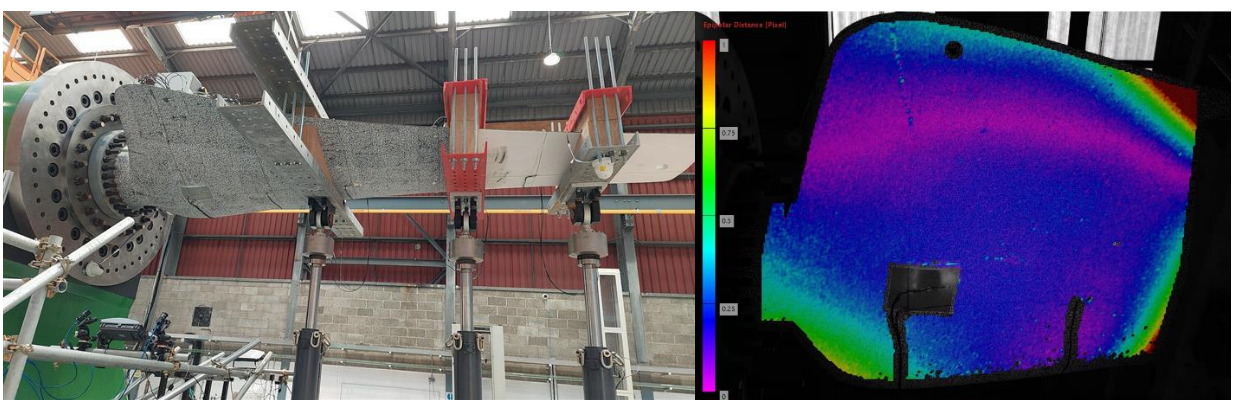

Fig. 1. General setup (left-hand). Distortion rate in pixels for a DIC field of view (right-hand).

Blade data

The blade (see Fig. 1) has a length of 5.25 meters and a weight of 1588.59 kg (15584.07 N). Its natural frequency is approximately 18Hz, and the NACA 63-4XX aerofoil series defines its cross-section. The thickness-to-chord ratio of the blade decreases from 55% at the root to a minimum of 18% at the tip. The innermost portion of the blade has a cylindrical cross-section with a thickness-to-chord ratio of 100%. This blade is a component of the DeepGen tidal project and was designed by Tidal Generation Limited (TGL) and manufactured by Aviation Enterprises Limited.

Method and Results

Digital Image Correlation. DIC is a non-intrusive optical technique which allows interpolation and generates an entire deformation field of the outer surface of any structure by tracking the movement of pixels in a camera image. In the case of a stereo setup, calibration is critical to correlate both cameras, using 150 high-resolution images with a target of 50-mm diameter dots. Calibration was done individually for every pair of cameras, and the average error was 0.0185 pixels. For the static test, DIC images were taken at 0.1Hz for a total duration of 6 hours. As for the fatigue test, another set of images was taken at 10Hz for small bursts every 30 minutes. This method resulted in 3,600 images during two days of fatigue testing. In the areas close to the edges, the field of view still gets distorted, as seen in Fig.1. This distorted field will not give accurate results for displacement or strain.

Tailored sensing. Tailored sensing is performed by choosing the location of the sparse strain sensors in a way that results in the best reconstruction of the strain map as recorded by the DIC. Considering a specific dataset of strain maps, we can limit the universal bases of all possible strain maps to an approximation based on a dimensionality reduction technique, e.g. singular value decomposition (SVD). The constrained measurement bases ψ_r contains the most significant eigenvectors obtained from the dataset using SVD, retaining its most important features. The measured values at the sparse locations y and the measurement bases ψ_r are related by Eq. 1:

$$y = C\psi_r a \tag{1}$$

Where C is a sparse vector giving the location of the measurements; $C \in \mathbb{R}^{p \times n}$, such that $p \ll n$ and a is the vector used for reconstruction [3]. We can optimise the location of sensors (C) by running pivoted QR factorisation on ψ_r [3].

Reconstruction. We use the previously collected dataset to compute the first few SVD terms and compute the optimal sensor location. We then record measurements of the reattached sparse strain gauges during static and fatigue tests. According to Eq. 1, with C , ψ_r and y known, we can then compute the value of the vector a . We then reconstruct the full-dimensional image by multiplying a with the existing dataset. This process allows us to define according to the number of sensors (pixels) we used the fidelity on the reconstructed strain map.

Conclusion

We proposed a methodology that can be applied to obtain the optimal sensor placement based on data collected by a DIC system and an MLA. This method identifies the locations according to the DIC resolution in which a sensor could give more relevant information that can later be extrapolated to reconstruct a full stain map partially. Moreover, we produced a dataset of DIC images and a pre-trained algorithm than can be used in further research.

References

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