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A Realistic Error Budget for Two Dimension Digital Image Correlation

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ABSTRACT

There has been a lot of interest in the matching error for two-dimensional digital image correlation (2D-DIC), including the matching bias and variance; however, there are a number of other sources of error that must also be considered. These include temperature drift of the camera, out-of-plane sample motion, lack of perpendicularity, under-matched subset shape functions, and filtering of the results during the strain calculation. This talk will use experimental evidence to demonstrate some of the ignored error sources and compile a complete "notional" error budget for a typical 2D measurement.

Keywords: Digital image correlation, full-field measurements, uncertainty quantification

1. INTRODUCTION

Uncertainty quantification (UQ) is important for any experimental technique including DIC. The level of confidence in a result is of key importance for making engineering decisions, whether this is for the measurement of material properties or simple displacement measurements of a structural response. The guiding document for UQ is the international "Guide to the expression of uncertainty in measurement" or GUM for short [1]. An important recommendation of the GUM is to first express mathematically the quantity being measured (measurand) as a function of all input quantities. For DIC, the input quantity is the image analyzed by the DIC code that leads to the measurand of displacements and strains. Unfortunately, understanding the errors of the image formation is complicated in itself. The flow of information and possible error sources in DIC are shown in Figure 1, beginning with the experimental setup, which includes the camera, lens, all the mounting hardware, and rather broadly the entire surrounding environment. While it is convenient and rather common to ignore all of these error inputs to the image, they are critical. The common assumption that the image is a perfect reflection of the underlying measurand is incorrect, with many researchers seemingly ignoring *everything* except the image correlation step. Evidence of this is shown by a quick survey of DIC literature where there are too many papers discussing an improvement of 0.0002 pixels using only synthetic images by providing slight modifications to the image correlation approach. With synthetic image studies have we missed the big picture? Is the image correlation mathematics still a relevant error source for a typical experiment?

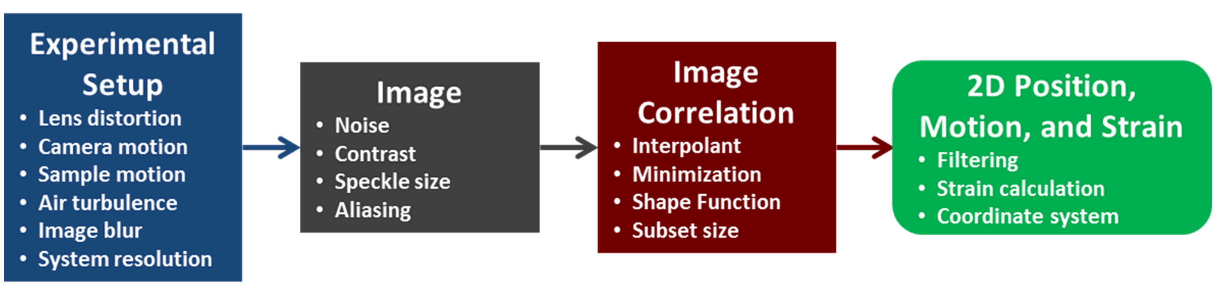

Figure 1. Data and error flow chart.

1. TYPE A VERSUS TYPE B UNCERTAINTY

1.1. Type A uncertainty assessment

The GUM expresses two types of standard uncertainty, Type A and Type B. Type A is a variance error that can be assessed via statistical means, that is, repeated measurements – or more colloquially the noise floor. For DIC, the noise floor is assessed by taking "stationary" images and running a correlation and looking at the resulting measurement statistics. It is important to note that this process is only effective at measuring the temporally and

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the spatially varying measurement issues. From Figure 1, included Type A uncertainties are the image noise, contrast, speckle quality, and air turbulence. It is obvious that many things from Figure 1 are not included in this measurement.

1.2. Type B uncertainty assessment

Type B uncertainty sources are rather broadly defined by the GUM as: "an estimate … that has not been obtained from repeated observations." For DIC, this includes synthetic image studies, DIC parameter studies, Monte Carlo approaches, and simulation of the experiment. Type B approaches are often used to investigate bias errors although they are not synonymous with bias errors according to the GUM. A typical bias error as defined by the GUM would be corrected, with any remaining uncertainty in the correction defined as a Type A uncertainty after correction. When applied to DIC, a bias error, due to the filtering of the strain calculation for example, often cannot be corrected, and there remains in many situations an error which is uncorrectable (i.e. the virtual strain gage (VSG) study does not converge, and the strain is unknown at some locations).

1.3. On the use of synthetic images

Unfortunately, the most common DIC UQ evaluation is the use of synthetic images. This is done because it is easy to do and maybe more importantly, the "true" answer is known. In contrast, the conundrum of experimental validation is that a complex mixture of error sources exist that can be very difficult to deconvolve. However it must be remembered that depending on the simulation approach, quite a few issues shown in Figure 1 *will not be* included when using synthetic images. Two examples include, air turbulence and sample motion; both of which may be an important contributor to the overall uncertainty. Therefore, in my estimation, the best use of synthetic images is to evaluate the fundamental limits of the DIC algorithms and to look at the influence of image artifacts. It is highly optimistic to assume that any given synthetic study will be an accurate assessment of the entire uncertainty of the DIC measurement.

This is not to say that modeling the experiment is an invalid approach to DIC UQ; in fact it is specifically included as a valid uncertainty approach in the GUM. However, most synthetic images seen by the author to this point are overly simplistic in their approach, and are likely to ignore important experimental error sources.

2. ERROR BUDGET OVERVIEW

Table 1 is a list of potential uncertainties for a 2D-DIC tensile test with a 100-mm field-of-view (FoV). This is a notional table that represents my estimates from 10 years of DIC experiments. It is important to remember that each DIC experiment may have a unique error budget, and this should be reflected in the estimates. Probably the most valuable exercise in assembling a table like this before taking data is to be able to better design your experiment. The challenging aspect of assembling this table is in assessing potential bias errors. Some are well understood and broadly published in the literature, for example the interpolant and noise bias errors [2-4]. The next sections describe some of the techniques listed in Table 1 that are used to assess the different uncertainty terms, if not discussed here, see the included references. The final point to keep in mind is that the DIC uncertainty should always be put in relation to the size of the measured signal, i.e. the signal-to-noise-ratio. With large sample responses, larger errors are acceptable. The most challenging situations are where you have a small signal in a difficult measurement environment.

2.1. Noise floor and extended noise floor measurements (lens distortions)

The noise floor is a simple approach for investigating a number of uncertainty parameters and it should be done for all experiments. The noise floor is found by taking a number of pre-test stationary images and analyzing them. An "extended noise floor" is even more useful and is obtained by translating the unloaded object through the FoV. This expands the uncertainty assessment from the image noise, lighting, speckles, etc. to include lens distortions, and camera and sample motion. This simple extension is easily done and should be included if practicable. Lens distortions can also be corrected via dot grids [5].

Table 1. List of error sources, assessment method and approximate magnitude.

2D Error Source	Type	Assessment Method	≈ |pixels|
Lens distortion	B	Either camera calibration (grids [5]) or speckle translation [6].	Pixels (w/o Calib.)
Camera motion	A,B	Noise Floor or static “dummy” region [7].	0.5
Sample motion	B	Dummy region [7] or other measurement method [8].	0.5
Turbulence	A,B	Noise floor (must have same environment as test)	0.01 to pixels
Image blur	B	Estimated from synthetic images	0.001
Resolution	B	Estimated via experiments and synthetic images	0.001 (contrast)
Image noise	A	Noise floor	0.01
Speckle contrast	A	Noise floor	0.01
Speckle size	B	Direct measure of speckle size [9], noise floor, parameter study	0.02 (w/o aliasing)
Aliasing	A,B	Noise floor	0.05
Interpolant	B	Synthetic and experimental image studies for optimum [10].	0.001 to 0.01
Minimization	B	DIC parameter study, synthetic and exp. image studies	0.005
Shape function	B	DIC parameter study, synthetic and exp. image studies	Linear fit
Subset size	B	DIC parameter study, synthetic and exp. image studies	Noise vs filtering
Filtering of results	B	DIC parameter study	Spatial resolution
Strain calculation	B	DIC parameter study	Spatial resolution
Coord. system	B	Other means	

2.1. DIC parameter studies

There are a number of DIC parameters, in the software settings, that can strongly influence the results. These can be studied in a systematic way to find the optimum compromise between filtering and noise suppression. Unfortunately increased filtering almost always compromises the spatial resolution, and this should be measured. For strain measurements this can be done with a virtual strain gage (VSG) study. By varying the VSG size and looking at the noise and maximum strain measured, an optimum compromise can be struck. The same types of studies can be done when looking at the subset size, shape functions and many other parameters available in the DIC codes.

2.2. Synthetic and experimental studies

There is still a strong need for synthetic images for studying DIC uncertainty [11-13]. This needs to be done with care to ensure that as many experimental error sources as possible can be captured in the simulation. I think there is an important future in the development and use of experiment simulation in optimizing experiments and estimating uncertainty.

3. UNCERTAINTY ASSESSMENTS

This section will briefly discuss a few sources of uncertainty that are often neglected – moving away from the usual interpolation, contrast and noise discussions. Discussion of other uncertainties can be found in the references in Table 1.

3.1. Camera motion

Motion of the camera in a 2D setup is obviously problematic and should be avoided by careful camera mounting, however, what is not often considered is motion due to camera heating [14]. Figure 2 shows an experiment where both the camera and the sample are rigidly mounted to a floating optical table and images are acquired over a 3 hour period. Different cameras and camera mounting configurations were studied. There is a strong correlation of both displacement and strain biases with the camera temperature, indicating that heating of the camera contributes to these bias errors. The difficulty with this type of error is that it will *appear* as a true strain when it is in fact an artifact of the change in the camera temperature. It is left to the reader to determine whether the SNR is acceptable for their current experiment. However, note that the bias errors in both the strain and the displacement shown in Figure 2 are well above the noise floor!

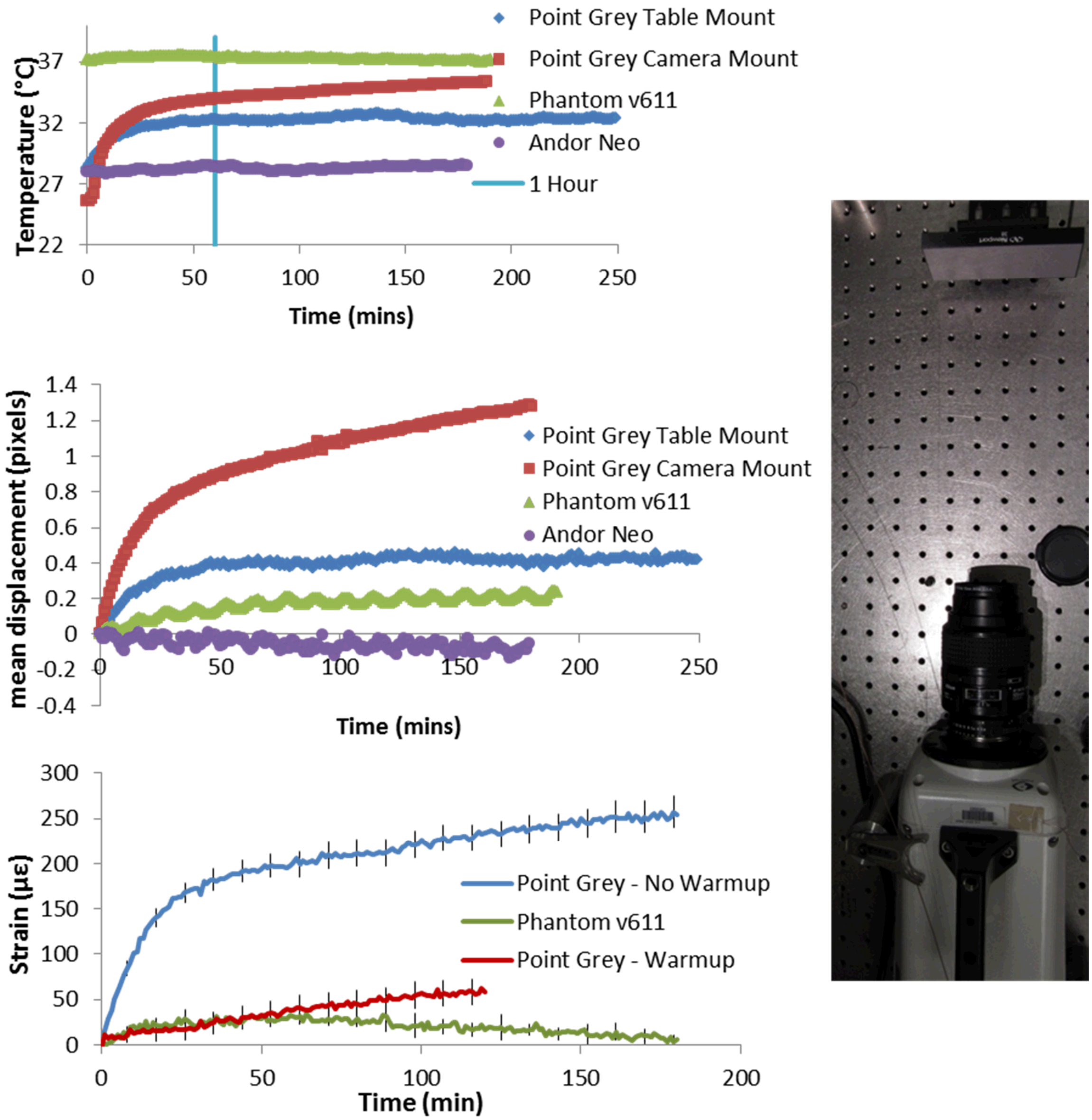

Figure 2. Static test for 4 conditions. Grasshopper Point Grey camera, Phantom v611 camera and Andor Neo cooled camera. (Top) Temperature of the cameras over 180 minutes. (Middle) v-displacement. (Bottom) principal strain biases, with the error bars representing the standard deviation (1σ), or noise floor, of the strain. (Right) Experimental setup with the Phantom v611 camera.

4. CONCLUSIONS

Understanding the total error budget for any experiment is critical. DIC is a simple and powerful tool for making measurements, however depending on the experimental arrangement, errors, and particularly bias errors can be a problem in 2D-DIC. For the success of a measurement, it is important that these error sources be evaluated.

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