# 2D and Stereo Digital Image Correlation Written in MATLAB

D. Atkinson[1a] and T.H. Becker[1]

[1]Department of Mechanical and Mechatronic Engineering, Stellenbosch University, Corner of Banghoek and Joubert Street, Stellenbosch, Western Cape 7599, South Africa

[a]17732913@sun.ac.za

**Abstract.** Although there are many publications documenting the theory of Digital Image Correlation (DIC), there is a lack of resources bridging the gap between the theory of DIC and its practical implementation as code. Two papers have been published, for 2D and Stereo-DIC respectively, which discuss the theory of a subset based DIC framework that is predominantly consistent with current state-of-the-art techniques, and explain how it is implemented as modular 117 line and 202 line MATLAB codes respectively. This aims to provide newcomers to the concept of DIC with the resources required to gain a deep understanding of DIC which is necessary to contribute to the field of DIC.

## Introduction

Digital Image Correlation (DIC) has become popular in experimental solid mechanics applications to determine the full-field displacements experienced by a specimen from images captured of it. However, despite its popularity, the DIC process is complicated, comprising of several intricate elements, and successful application of DIC requires an understanding of all of these elements. To this end there are several publications which provide a comprehensive discussion of the mathematical theory of DIC [1] which along with the good practices guide [2] provides newcomers to DIC with sufficient knowledge to apply DIC successfully. However, in order to contribute to the field of DIC, by improving DIC for established applications or extending its use to novel applications, requires a deep understanding of DIC. Gaining such a deep understanding is cumbersome due to the lack of resources which directly bridge the gap between the mathematical theory of DIC and its coded implementation. More specifically, although some papers provide code consistent with the theory presented [1], these codes focus on robustness and ease of use which, despite making them more suited to real world applications, makes them ineffective as a learning resource.

This lack of resources acts as a barrier to newcomers intending to further the capabilities of DIC, thereby limiting the development rate of the field. It is for this reason that the authors have published two papers, for 2D [3] and Stereo-DIC implementations [4] respectively, which bridge the gap between the theory of DIC and its practically implementation as MALAB code. This is achieved by presenting the theory of a subset based DIC framework, that is predominantly consistent with current state-of-the-art techniques as identified by Pan [5], and detailing how the framework is implemented as a 117 line 2D-DIC (ADIC2D) and 202 line Stereo-DIC code (ADIC3D).

## Introduction

Stereo-DIC determines the in-plane and out of plane displacements experienced by the specimen from image pairs capturing the specimen simultaneously from different views. In contrast, 2D DIC determines the in-plane displacements of the specimen from images capturing a single view of the specimen. DIC consists of three main tasks: calibration, correlation (used for temporal and stereo matching) and displacement transformation. Both implementations perform calibration according to Zhang's method [6]. Furthermore, both make use of the inverse compositional Gauss-Newton optimisation method to find the shape function parameters (SFP) which minimise the zero-mean normalised sum of squared difference correlation criterion (in order to perform correlation). For temporal matching, utilised by both ADIC2D and ADIC3D, the Phase Correlation Method is used to determine SFP initial estimates. For stereo matching, exclusive to ADIC3D, the scale-invariant feature transform [7] feature matching method is used to obtain SFP initial estimates.

Displacement transformation translates the pixel displacements within the images, determined by correlation, to metric displacements in the real world. ADIC2D makes use of the inverse of the camera model used during calibration to transform the displacements. ADIC3D uses both the polynomial and linear triangulation methods [8] to determine the 3D metric displacements experienced the specimen.

The novelty of the framework is its modularity which is threefold. Firstly, each main task is performed by a separate subroutine resulting in an open-source code that is in the form of an open framework. This allows the reader to progressively build up their understanding of the code by considering one subroutine at a time and makes understanding the link between the code and theory straightforward. Additionally, this allows the user to easily change the code according to their needs, which coupled with the validation of the code, makes it attractive as a starting point to develop the capabilities of DIC.

Secondly, the shape function (SF) order, image filtering parameters and interpolation method can be easily changed enabling the reader to investigate how these affect the computed displacements in the practical manner. Thirdly, the SF order, subset shape and subset size can be assigned on a per subset basis. This facilitates easy coupling with adaptive strategies in order to assign these parameters to each subset such that they are most appropriate for the speckle pattern and deformation that the subset is attempting to track. This is reasoned to be valuable because adaptive subset size and SF order selection was identified by Pan [5] as one of the main remaining problems for subset based DIC.

## Validation

ADIC2D was validated using samples 1, 2, 3 and 14 of the SEM 2D DIC Challenge [9] while ADIC3D was validated using Samples 1, 2 and 5 of the SEM Stereo-DIC Challenge [10]. Here the results for Sample 14 of the SEM 2D DIC Challenge are presented because they reflect the capabilities of the correlation aspect of both implementations of the framework. The errors are reported as the root-mean square error (RMSE) and standard deviation (STD) indicating the precision and accuracy respectively. Sample 14 contains a sinusoidal displacement field with increasing frequency to investigate how the code compromises between noise suppression (STD) and spatial resolution (SR). In accordance with [9] SR refers to the highest frequency, of the sinusoid, at which the code is capable of capturing the peak displacement and strain within 95% and 90% of the true values respectively. Table 1 presents the results for subset sizes of 31, 51 and 71 pixels (to reflect how the subset size affects the compromise between SR and noise suppresion) using the first-order SF along with the results for code A and G which were the best codes in terms of noise suppression and SR respectively [9]. The framework applied Gaussian filtering to the images with a window of 5 pixels and a Gaussian distribution with a standard deviation of 0.4. SR is reported as the period in pixels so that smaller values indicate better performance for all the tabulated metrics. It can be seen that ADIC2D has precision, accuracy and SR falling in-between codes A and G. Thus, it performs with sufficient precision and accuracy to be considered reliable enough for use in experimental solid mechanics applications.

| Code/subset size | Displacement | | | | Strain | | | |
|---|---|---|---|---|---|---|---|---|
| | RMSE [pix] | Variance [pix] | Max Bias [pix] | SR [pix] | RMSE [pix/pix] | Variance [pix/pix] | Max Bias [pix/pix] | SR [pix] |
| Code G | 0.010 | 0.010 | 0.012 | 100 | 453 | 429 | 923 | 74 |
| ADIC2D 31 | 0.014 | 0.013 | 0.017 | 160 | 600 | 335 | 1674 | 182 |
| ADIC2D 51 | 0.014 | 0.007 | 0.033 | 257 | 839 | 193 | 2720 | 233 |
| ADIC2D 71 | 0.022 | 0.005 | 0.059 | 354 | 1255 | 125 | 4412 | 294 |
| Code A | 0.022 | 0.005 | 0.056 | 716 | 1131 | 172 | 3399 | 410 |

**Table 1 –** Noise suppression vs spatial resolution results for ADIC2D for Sample 14

## Conclusion

Although these paper does not contribute novel theory to the field of DIC, it attempts to improve upon one of the barriers that is potentially limiting the rapid advancement of the field. More specifically, although the theory of DIC is well documented in literature, there is a lack of resources which attempt to bridge the gap between its theory and practical implementation as code. This acts as a barrier to newcomers intending to gain the deep understanding necessary to contribute to the development of DIC. In addition to serving as an educational resource, the modularity of the code coupled with its validation makes it attractive as a starting point to develop the capabilities of DIC.

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