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Research Paper

Vermiculate artefacts in image analysis of granular materials

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ABSTRACT

Some reported analyses of images of deforming granular materials have generated surprising vermiculate strain features which are difficult to reconcile with the mechanics of deformation of granular matter. Detailed investigation using synthetic images and improved processing of images of laboratory experiments indicates that such features can emerge as a consequence of the image acquisition (sensor, contrast, resolution), the subsequent image correlation implementation, and the user's choice of processing parameters. The two principal factors are: (i) the texture and resolution of the images and (ii) the algorithm used to achieve sub-pixel displacement resolution. Analysis of the images using a sub-pixel interpolation algorithm that is more robust than that used originally eliminates the vermiculate features for images with moderate resolution and texture. However, erroneous features persist in images with low resolution and poor texture. Guidance is provided on ways in which such artefacts can be avoided through improved experimental and image analysis techniques.

1. Introduction

Image analysis has become a widely used tool for obtaining full-field information of displacements in granular media. The process starts with the design of an experiment that allows the acquisition of digital images of the deforming material (e.g. behind a transparent window) at chosen intervals. Example experimental setups have been described for element testing [4], large scale 1 g testing [40] and centrifuge testing [28]. Similar equipment has been used to capture images to investigate a wide range of geotechnical phenomena, including: the development of shear bands in sands [23]; seasonal rainfall-induced slope failures [33]; the effects of tunnelling in sand on greenfield settlements [14]; and fault rupture propagation in sand [2].

Several image processing techniques have been developed to deduce displacements from analysis of successive images captured using such experimental apparatus, e.g. image subtraction [10,24], particle tracking [7,3] and image correlation techniques such as Particle Image Velocimetry (PIV) [38,41] and Digital Image Correlation (DIC) [31]. With adequate image texture (the number and contrast of spatial features and/or grains), image correlation techniques are most suitable for obtaining accurate displacement fields with high spatial resolution.

However, it is not trivial to retrieve meaningful displacement data from such experiments. The quality of the image texture (or speckle pattern) is typically dictated by: (i) the natural contrast of coarse grained material or the artificial seeding applied to the surface of the specimen that is visible to the digital camera through a transparent window (which is dependent on the scale or resolution of the image because this determines how well individual grains can be distinguished); (ii) the image acquisition process (sensor, lens, illumination, field of view and image capture frequency); and (iii) any image pre-processing applied prior to the displacement computations. In addition, the image correlation algorithm chosen to compute the displacements needs to be carefully selected in order to avoid numerical artefacts in the image analyses.

Muir Wood and Leśniewska [15] and Nazhat and Airey [16] provide examples of analyses that have potentially been affected by erroneous numerical artefacts that appear in the strain fields computed from the displacements as highly concentrated bands of shearing. Such features are difficult to reconcile with the mechanics of deformation of granular matter. This paper aims to provide guidance on the selection of the most influential experimental

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parameters in order to avoid spurious features and presents some examples of features that might arise for ill-chosen conditions.

2. Image correlation: a brief description

The tools employed in geotechnical applications of image analysis have either been developed within the community [41,9] or have been borrowed from adjacent disciplines, e.g. open source PIV tools such as MatPIV [32], PIVlab [35], OpenPIV [34] and JPIV [37]. Meanwhile developments in experimental mechanics and fluid mechanics continue [17,25].

The ability to extract displacement fields from image correlation rests on four implicit assumptions [1]:

– The particles that are observed are homogeneously distributed across the image. This will usually be automatically satisfied for sands, where the individual grains often contain sufficient natural colour variation to provide adequate contrast. For clay models individual particles are not visible and a (homogeneous) surface speckle has to be added by artificial seeding.
– The observed natural or imposed image texture provides a perfect representation of the displacement of the soil. Wall friction may make the observed displacements unrepresentative of the displacements occurring through the thickness of the material.
– The 'reference' and 'target' images are sufficiently similar (i.e. the deformation is small enough) that a spatial measure of correlation can be computed and a clear peak isolated for all subsets (also known as patches or interrogation windows).
– The shape (or warp) function (which mathematically describes how the subset is allowed to displace and deform during the displacement computation) used by the image correlation algorithm should be consistent with the deformation being measured. Simpler correlation algorithms assume that the transformation from 'reference' to 'target' is a pure translation; more sophisticated algorithms may accept distortion or rotation in addition to translation.

Most freely available PIV/DIC algorithms, including those referenced here, perform two separate computations: (i) selection of a subset within the 'reference' image for which the peak in cross-correlation can be sought in successive 'target' images, for each subset, to the nearest integer pixel coordinates; and (ii) refinement of this measurement by interpolation of the cross-correlation for the subset corresponding to the correlation peak and a selection of its neighbours in order to refine the displacement measurement to sub-pixel resolution. Algorithms which employ a zero-order subset shape function which only permits the subset to be translated when seeking to maximise the cross-correlation cannot accommodate significant distortion or rotation. Large gradients of displacement across the subset being interrogated can lead to an inability to correlate 'reference' and 'target' images, inevitably resulting in measurement errors.

2.1. Cross-correlation of the subsets

Subsets of an initial 'reference' image are compared with subsequent 'target' images in order to calculate a spatial measure of cross-correlation (CC) (see Fig. 1). Two popular measures are 'normalised cross-correlation' (NCC) [13] and 'zero normalised cross-correlation' (ZNCC) [20]. The zero normalised cross-correlation coefficient (CC_{ZNCC}) represents a robust measure of correlation as it can accommodate variations (offset and/or scale) in brightness across the image, with values of 1, 0 and -1 indicating perfect, zero and inverse correlation, respectively. Mathematical definitions for CC_{ZNCC} and other measures used throughout this paper are provided in the Appendix A.

2.2. Sub-pixel displacement refinement

The integer displacement estimate from the first step is refined using sub-pixel interpolation functions. Typically bi-cubic splines or Gaussian functions are fitted to the correlation peak and the neighbouring values (Fig. 2). The maximum value of the interpolant provides an improved estimate of displacement typically to sub-pixel precision of the order of $0.01p$ [41], where p is the pixel size.

More sophisticated sub-pixel displacement refinement can be achieved by incorporating more complex basis spline curve-fitting of the interpolation peak [11]. Alternatively, a higher-order subset shape function that allows the displacements within the subset to vary linearly or non-linearly for first- and second-order shape functions respectively [42], could be incorporated. Methods with higher-order subset shape functions tend to deal with spatially varying deformation fields more robustly but require additional image intensity interpolation and optimisation techniques and have until recently not been widely available. Ncorr [5] and GeoPIV-RG [27] are two recently developed examples of PIV/DIC software which incorporate such an enhanced sub-pixel displacement refinement and which are now freely available to the geotechnical research community.

3. Requirements for accurate cross-correlation

The following design rules are based on experiences in fluid mechanics using PIV to analyse the trajectories of tracers in fluid flow (e.g. [1]), DIC analysis of a speckle pattern on a material surface (e.g. [30]), and recent experience of performing PIV/DIC analyses on various laboratory geomaterials (e.g. [28]).

R1 *Image quality:* A large Signal-to-Noise Ratio (*SNR*) (see Appendix A for definition) using the full dynamic range of the image sensor is desirable. Provide sufficient and uniform illumination of the specimen. Use high quality optics characterised by a small available *f*-stop (absence of optical aberrations); then set aperture with the highest value of *f*-stop (smallest aperture size) compatible with the available illumination and desired depth of field. Select a camera with a global rather than rolling shutter, and with a Charge-Coupled Device (CCD) sensor rather than a Complementary Metal Oxide Semiconductor (CMOS) sensor [28]. Images with a uniform distribution in the intensity histogram with values between 20 and 225 are considered high quality for an 8-bit sensor (maximum 255 intensity levels). Values lower than 20 are often associated with sensor noise, whilst values above 220 are approaching sensor saturation [30]. Image formats with high compression will reduce the *SNR* of the image (e.g. [6]). Uneven or fluctuating illumination has a large impact on the subsequent analysis if non-normalised cross-correlation is used (e.g. [36]). Quantitative assessment of global image quality can be provided by checking the Mean Intensity Gradient (MIG) proposed by Pan et al. [18].

R2 *Information in the signal:* The spatial resolution of the digital image data, stored in a pixel array, where each pixel holds an intensity value for the amount of light that fell on that pixel, is discrete. Hence, there should be a sufficient number of pixels in the spatial feature that needs to be followed, for example the grain, in order to retain enough information in the signal. Theoretical and experimental analysis from