3D Digital Image Correlation: The Ultimate Biomechanics Tool for Displacements and Strain Testing

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Abstract

3D Digital Image Correlation (DIC) provides the ability to measure non-contact 3D coordinates, displacements and strains of materials and structures. Although widely accepted in mechanical engineering and materials engineering, this tool as yet to prove its capability within the biomechanics industry with soft tissues, bones and most medical-specific materials. Known for its unique capability to be used for rapid full-field measurements from material characterization to full component testing, providing the equivalent of the results of over 10,000 contiguous strain gauges or displacement sensors, this technique is now recognized and certified (NIST, Boeing...) as equivalent to standard mechanical testing tools in the aerospace and automotive industries. 3D DIC is used across industries for improving the quality and the accuracy of the data collected to best understand mechanical behaviors of components or validate FEA models. This work focuses on the integration of the DIC technology with load frame such as Instron, MTS and Zwick for simple coupon testing of soft tissues, implants and prostheses. It was shown that DIC could in fact provide a more flexible measurement platform with capabilities for any coupon size, very small to large strains with a single instrument as well as multi-axial data in every direction for each and every one of the biomechanics applications evaluated.

Introduction

Since the 1980s, camera sensor innovations have unlocked new potentials for the testing industry. One of those new concepts, Digital Image Correlation (DIC), was introduced almost 40 years ago aiming to improve data quality and integrity (Rizzuto, Carosio, & Prete, 2014). However, due to computational power and still relatively limited camera sensor capabilities, it mainly grew in the academic environment. When camera and computer capabilities reached new highs in the 2000s, the technology's ability to measure non-contact 3D coordinates, displacements and strains of any material became so powerful for it to finally bloom in many other industries. As (Palanca, Tozzi, & Cristofolini, 2015) stated, pointwise measurements are often insufficient to fully monitor an experiment. In those cases, string potentiometer, linear actuators and other displacement transducers as well as strain gauges, extensometers and various strain measurement devices, fall short of providing a complete understanding of the test object. Full-field tools really are the only option in such environments in order to assess and identify local damages, such as a cracks or other "hot-spots". For biomechanics, such tests are critical to characterize organs, biological tissues, and biomedical devices. Indeed, the ratio between the load and the displacement of a component lead to its stiffness and are essential for many biomechanical tests; bone remodeling and bone fracture are both tests driven by a stress-strain analysis. Moreover, the inhomogeneous and anisotropic properties of most biological specimens require full-field data and non-contact techniques powered by optical camera systems such as DIC are vital to improve the innovation process. On another note, finite element (FE) analysis, based on computational models techniques, are increasingly popular and most users tend to overlook the importance of validation of verification of the results generated with FE analysis. Fact is, experimental data must be used as an input and we can't emphasize enough that these models must be validated against experimental tests (Ivatury, Knight, & Shivakumar, 2015).

Differences with traditional measurement techniques

The type of data collected with Digital Image Correlation systems stands out when compared to the traditional techniques. The major differences lies in the shifts from temporal to spatial data quality and from analog to digital data collection. This first change is often translated by the terms "full-field". Indeed, since traditional techniques lead to single data points, they typically fail to generate meaningful insights of the entire test object. Time and again, we've seen experiments with a combination of DIC, strain gauges and displacement transducers where the traditional sensors where expected to be at the maximum loading locations. Unfortunately, the predictions for these locations often fail short and it falls to the DIC data set to provide data for the actual hotspot just a few inches away (Liebherr-Aerospace, 2016). In biomechanics, the ability to collect data without the need to predict the failure area or define the region of interest beforehand is even more critical (Abbasi, et al., 2018). However, that shift to spatially-rich data collection using DIC comes at a temporal expense. Indeed, traditional gauges connected to a signal amplifier and data acquisition system will typically excite and collect information a few thousands times per second (>1kHz). It then average the data received and refresh the output at 10-100 Hz, typically allowing for simple temporal filtering and reduction of the noise-to-signal ratio. A simplified statement would be that the choice is between acquiring a thousand value at a one location (traditional) or acquiring a single value for a thousand location (DIC) every second.

The second shift from analog to digital means that the data is no longer generated by passing a current thru the physical instrument and measuring the electric potential difference or current variation. This major difference is often translated by the "non-contact" capability of DIC systems. As mentioned before, the change is instead monitored thanks to a passive pattern applied to the surface of the part. The digital sensor of the camera is instead responsible for the data generation. This difference also leads to independence of the measuring system to the length of cables between the sensors and the acquisition system, number of available channels, isolation of the measured signals, signal drift or signal scale and saturation issues. More importantly, the raw data, the pictures, is typically saved and can be processed at the end of the test, which allows the user to define the points of interest at the end of the test and retroactively measure the data. These differences are highlighted by Palanca *et al.* (2015) and identified as critical for biomechanical testing. They simply refer to them as: "full-field measurement […] for a more complete description of the behavior of biological specimens", "contactless measurements […] particularly important for deformable materials such as soft tissues" and "relatively simple preparation compared to [traditional] measurement techniques". They also highlight that "such features are mandatory for typical biomechanical tests on non-homogeneous and anisotropic materials, and specimens with a complex geometry" (Palanca, Tozzi, & Cristofolini, 2015).

History of Digital Image Correlation

Digital Image Correlation was first introduced back in the 1980s in the United States and eventually productized in the late 1990s for commercial applications (Chu, Ranson, Sutton, & Peters, 1985) (Tyson, Schmidt, Coe, & Galanulis, 2005). It truly soared in the 2000s with significant advancements in the biomechanics field (Zhang & Arola, 2004). A comprehensive list of publications and applications is presented in an industry review published in 2015 by Palanca *et al.* This list certainly highlight the prolific developments of the first decade of the century using DIC, but these experiments were often conducted using home-written Digital Image Correlation algorithms. With the rise in popularity of DIC, commercial platform, like ARAMIS by GOM GmbH, gained in popularity and many popular software suites added libraries to perform (especially 2D) DIC. Such is the case for MATLAB (MathWorks, Natick, MA, USA) and Mathematica (Wolfram, Champaign, IL, USA). An impressive number of universities world-wide also developed their own code in order to perform these experiments. The robustness, confidence and quality of these home-written algorithms is rarely high and often serve mainly an academic purpose for students to develop their understanding of DIC.

However, in the wake of all these developments, an international independent engineering society was born. The International Digital Image Correlation Society (iDICs) is composed of members from academia, government and industry and notably published their Good Practices Guide in October 2018 hoping to provide guidelines to evaluate and improve home-made algorithms (A Good Practices Guide for Digital Image Correlation, 2018). They are also developing world-wide certification programs to improve industry techniques and practices while working on DIC standards with regulatory bodies.

Basic principles of DIC

Put simply, a pair of high resolution digital cameras are aimed at the object to be tested. 3D DIC then uses photogrammetry to determine the relative location of the two cameras in 3D space and combine the two images in a 3D environment. A random or regular pattern with good contrast is typically applied to the surface of the test object. That pattern deforms along with the object and is the main input for the algorithm to track expansion or compression of the material's surface (Chu, Ranson, Sutton, & Peters, 1985). As the deformation of the structure, usually at various load conditions, is recorded by the cameras, it is correlated from the left to the right camera. The initial correlation process defines areas known as facets, typically 5-25 pixels square (Amiot, et al., 2013), across the region of interest. The center of each facet is used as a node in a mesh that covers the entire surface area. It is important to note that every facet is tracked in each successive image with sub-pixel accuracy. As explained by (Tyson, Schmidt, Coe, & Galanulis, 2005), using photogrammetric principles, the 3D coordinates of each node are precisely calculated. They are also computed for each load condition, also known as a stage. These nodes can obviously be inspected for their displacement in X, Y and Z between each stage, but can also be inspected for their relative motion to surrounding nodes. Effectively, these nodes therefore contain strain information, how much the distance separating two neighboring nodes increased (or decreased) between stages. In other words, the DIC results are the 3D shape of the component, the 3D displacements, and the plane strain tensor.

An example of a commercial image correlation system configured for 3D measurement during a tension test is shown in Figure 1 below. Typically, a camera bar is mounted to a tripod or a stand on wheels and the sensor head is simply placed in front of the test sample at the correct working distance. This setup can easily be combined with a servo-hydraulic machine (or an electric screw load frame) since rigid body motion has no effect on the strain measurements (Yoneyama, Kikuta, Kitagawa, & Kitamura, 2006). A standard setup also includes lighting. Most commercial systems use powerful LEDs mounted on the camera bar.

Figure 1: ARAMIS 3D DIC system aimed at a tensile coupon on a Zwick load frame.

Patterning

Digital Image Correlation works only when the surface of interest provides a pattern that can be identified and tracked by the algorithm. In some cases, the surface naturally has all the required elements of an adequate pattern. These requirements are: (1) high contrast, (2) random distribution, (3) balanced black/white ratio (50/50) and (4) uniform. In other words, the pattern should not be repetitive, black (or white) should not be dominant, grey/blurry areas should not be present and should not be more dense in certain areas (Rizzuto, Carosio, & Prete, 2014) (Tyson, Schmidt, Coe, & Galanulis, 2005). One final requirement plays a big role, the size of the dots. The ideal size is usually defined in pixels and therefore the size is dependent on the defined measured area, also as known as the field-of-view (FOV), and the resolution of the cameras. Figure 2 shows a typical pattern applied to a tensile specimen. Since the ideal dot size diameter is optimal at roughly 5 pixels, the resolution and size of the measuring areas determine the actual size of the dot in millimeters (Palanca, Tozzi, & Cristofolini, 2015). For example, a 5 Megapixels camera could have a resolution of 2,450 pixels by 2,050 pixels. If the system is setup for an area of 100mm by 85mm, this leads to each pixel being 0.04 mm long (= 100mm/2450px). Aiming for 5 pixels per dot, the ideal pattern size would be around 0.2 mm per dot. Therefore, if the desired measurement window is larger, the corresponding area covered by each pixel (for a given sensor resolution) is also larger. As such, the speckle pattern dots would require a bigger diameter. Now, in order to obtain the best speckle pattern for a specific application, the dimension of the speckle should be defined for that application.

Creating that speckle pattern isn't and shouldn't be a challenge considering the previous work done. The most common techniques used are high-contrast spray paint (sometimes an airbrush is used for smaller pattern), graphite/toner powder dispersed on the specimen or pre-defined markers as shown in Figure 3. As shown by Abbasi *et al.* (2018), the graphite technique works very well, especially for soft tissues. Ink dyes can also be used, but Abbasi *et al.* showed in their experiment that synthetic graphite powder had less effect on the mechanical properties of soft tissues when compared to the ink dyes. Moreover, their graphite pattern technique survived on fully immersed transcatheter aortic valve (TAV) being tested in an in vitro setup using a saline-solution.

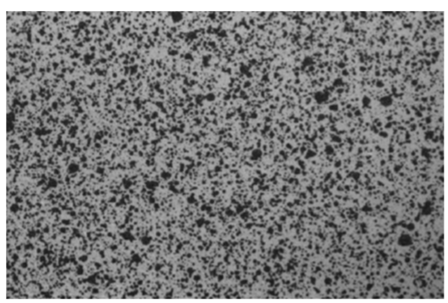


Figure 2: Digital Image Correlation speckle pattern example.

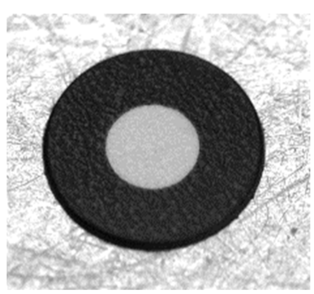


Figure 3: Standard uncoded target marker from GOM GmbH for displacement measurements.

DIC Parameters

Since this measurement technique relies heavily on the algorithm results, it must be highlighted that the best results depend on critical parameters typically defined by the user based on each specific application or test campaign. These parameters must be defined with care and we can't underestimate the relevance of a pre-test campaign to determine and validate the ideal parameters. Each measurement should mention the core parameters used and why they were defined as such. The Good Practices Guide for Digital Image Correlation published by the International Digital Image Correlation Society covers these very well (2018). Different publication uses different nomenclature for those core parameters, but we will simply list the essential ones as defined by the iDICs:

- Subset size is the dimension of each sub-image used for calculation;
- Step size is the distance between two subsets and controls the density of points;
- Thresholds determine the quality and confidence results for each subset and typically include limits for the matching criterion between left and right as well as for the epipolar error;
- Virtual Strain Gauge (VSG) area is defined by the strain tensor neighborhood size and determines the area (and number of surrounding nodes) used to calculate the strain field.

Again, these values determine the accuracy, precision and spatial resolution of the data set (Palanca, Brugo, & Cristofolini, 2015). Due to inherent flexibility and numerous possible uses of DIC, a universally optimal set of parameters does not exist, particularly in biomechanics. As stated by Palanca *et al.*, a choice must be made in relation to the specific application (i.e. tissue, anatomy and dimensions of the specimens).

Biomechanics applications

3D Digital Image Correlation (DIC) is an incredibly versatile measurement technique and provides tremendous advantages in the biomechanics field (Tang, Liang, Xiao, Guo, & Hu, 2010). It's ability to measure so many different materials such as hard and soft biological tissues independently of their particular mechanical behavior is remarkable. Since DIC is agnostic to the ductile/brittle, isotropic or anisotropic and in/homogeneous properties, it is an ideal tool to measure either small or large biomechanical deformations.

Where soft tissues used to be measured using extensometers, significantly influencing the response of the material, and then replaced by optical extensometers, we couldn't effectively gain sufficient insights during a test since the measurement only provided general strain over a large surface area. The local strain distribution were not available and large displacements often led to inaccurate measurements (Palanca, Tozzi, & Cristofolini, 2015). The TAV study by Abbasi *et al.* is a wonderful example of DIC benefits, but so are the Moerman *et al.* (2009) on silicon gel and the human tendon tissue analysis performed by Luyckx *et al.* (2014). These tests are also easily integrated with a standard load frame and load values can be combined with the full-field data set to calculate local stress mapping or generate stress-strain curves in a single measurement platform. As shown by Abbasi *et al.*'s work (2018), in vitro application of DIC can successfully measure the strain distribution in various components of the cardiovascular system. Digital Image Correlation's potential to improve the understanding of pathologies and deliver better treatment is outstanding. However, only a well define implementation of DIC with a universal test machine (MTS, Instron, etc.) will provide sufficient data integrity to calculate the state of stress/strain considering the inherent pseudoelastic nature of soft tissues and the, usually, small dimensions of the test specimens. That being said, multi-axis test machines could further enhance the quality of results by allowing an easier reproduction of the physiological working condition.

Recently, we also saw tensile testing of cranial cruciate ligament (CrCL) in adult cattle. A more detailed review of soft tissues applications can be found in Palanca *et al.* (2015).

For hard tissues, the most common material is obviously bones and previous measurements were often performed using strain gauges since their impact on the mechanical properties are typical much less damaging in comparison to the soft tissues. This assumption was however addressed in the past and the reinforcement was shown to not be negligible in some cases (Ajovalasit & Zuccarello, 2005). As stated before, the other common problems encountered are the premature failure of the strain gauges for large deformations and only provide data at the discrete location where they were bonded. Extensometers (and optical extensometers) have also been used, but, like soft tissues, these only provide global strain data and fail to inform on the local strain distribution. Other traditional techniques are generally synonymous to long setup installation and specimen preparation. Therefore, implants and bones typically benefit tremendously from using Digital Image Correlation measurement techniques. In fact, multiple experiment, such as Sztefek *et al.* (2009), demonstrated that the spatial resolution of strain gauges was simply inadequate to measure localized peak strains. Sztefek *et al.* notably worked on mouse tibia under axial compression. Then, Tyson, Schmidt and Galanulis (2003) also discussed testing of many hard tissues such as ionic polymeric artificial muscle, tendons and ligaments. Single trabeculae of cancellous bone as well as cortical bone and even teeth were all successfully measured using DIC techniques. Nickel titanium rods with variable stiffness for spine stabilization (Brailovski, Facchinello, Brummund, Petit, & Mac-Thiong, 2016) as well as spine implants have also attracted a lot of attention recently leveraging DIC measurement techniques.

Leverage DIC for Finite-Element validation

Another extremely valuable feature of DIC is its ability to feed, validate and, sometimes, compare experimental data with numerical simulations. DIC is often leveraged to (1) identify model parameters such as the material properties, (2) full-field validation of model predictions, (3) improve DIC parameters definition (i.e. identifying filters size and optimal subset step), (4) inverse material characterization (i.e. feeding the mechanical response to a model in order to estimate the hyperelastic skin conditions). A very simple comparison example is shown below in Figure 4 for a wrench with a torque loading. Here, full-field deviations computed show variations between the experiment and the predictions. These were found to be tied to poor boundary conditions in the FE model as the bolt was not in full contact with both edges. Rather, the slightly smaller bolt created strain concentration at the contact points generating non-symmetric strain conditions.

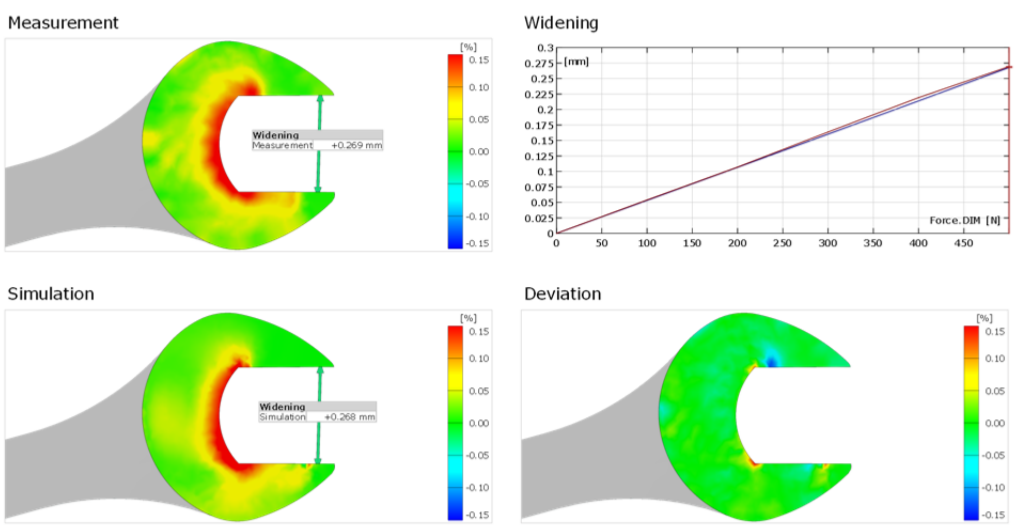
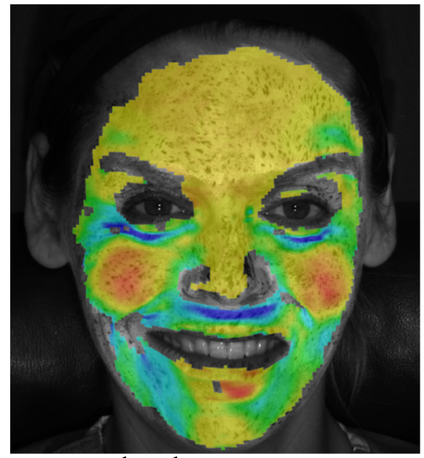
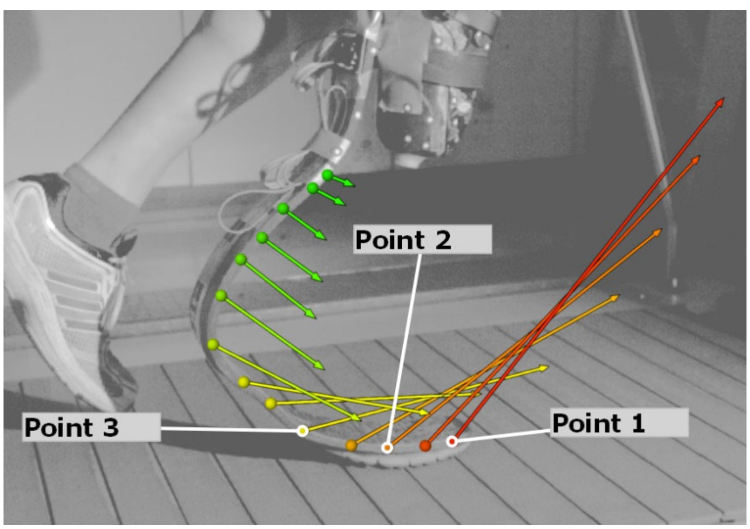


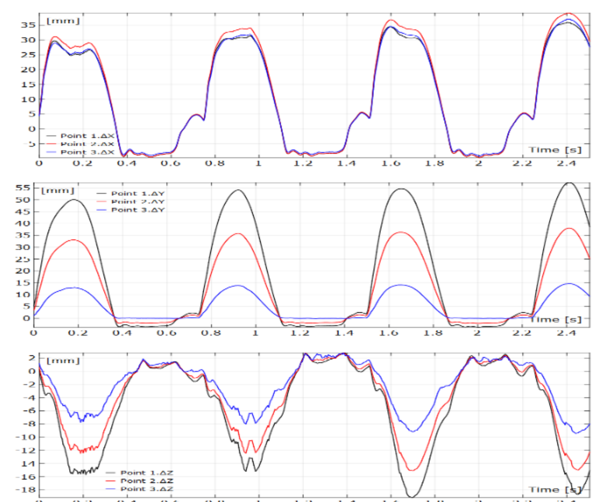
Figure 4: Comparison ARAMIS 3D DIC data and FEA results on a wrench torque loading.

Conclusion

3D Digital Image Correlation (DIC) provides the ability to measure non-contact 3D coordinates, displacements and strains of materials and structures. Widely accepted in mechanical engineering and materials engineering, it was shown that DIC could in fact provide a very flexible measurement platform with capabilities for any coupon size, very small to large strains all performed with a single instrument. This proved itself true within the biomechanics industry with both soft and hard tissues, bones and many medical-specific materials for each and every one of the biomechanics applications evaluated. 3D DIC is used across industries for improving the quality and the accuracy of the data collected to best understand mechanical behaviors of components or validate FEA models. Integration of the DIC technology with load frame such as Instron, MTS and Zwick for simple coupon testing of soft tissues, implants and prostheses is also very attractive considering the rich and quality data generated by such systems. As a full-field, contactless and versatile technique, DIC was successfully utilized for various biomechanical applications. As stated, DIC can measure displacements with very high accuracy and precision, but great care must be shown to compute accurate and precise measurements. Both the surface preparation and the algorithm settings were shown to be critical to the success of a DIC experiment. However, thanks to the versatility of Digital Image Correlation, we foresee an increase in the number of applications developed in the biomechanics field, both in vivo and in vitro.







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