Benchmarking of depth of field for large out-of-plane deformations with single camera digital image correlation

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ABSTRACT

A problem that arises when performing stereo digital image correlation in applications with large out-of-plane displacements is that the images may become unfocused. This unfocusing could result in correlation instabilities or inaccuracies. When performing DIC measurements and expecting large out-of-plane displacements researchers either trust on their experience or use the equations from photography to estimate the parameters affecting the depth of field (DOF) of the camera. A limitation of the latter approach is that the definition of sharpness is a human defined parameter and that it does not reflect the performance of the digital image correlation system. To get a more representative DOF value for DIC applications, a standardised testing method is presented here, making use of real camera and lens combinations as well as actual image correlation results. The method is based on experimental single camera DIC measurements of a backwards moving target. Correlation results from focused and unfocused images are compared and a threshold value defines whether or not the correlation results are acceptable even if the images are (slightly) unfocused. By following the proposed approach, the complete DOF of a specific camera/lens combination as function of the aperture setting and distance from the camera to the target can be defined. The comparison between the theoretical and the experimental DOF results shows that the achievable DOF for DIC applications is larger than what theoretical calculations predict. Practically this means that the cameras can be positioned closer to the target than what is expected from the theoretical approach. This leads to a gain in resolution and measurement accuracy.

1. Introduction

1.1. DIC

The term digital image correlation refers to the class of non-contact measurement methods that acquire surface images of an object, store them in digital form, and perform image similarity metrics to extract full-field shape and deformation data [1]. It allows for a sub-pixel measurement accuracy of displacements and strains on the surface of complex parts. To be able to perform stable and sub-pixel accurate correlation, a random, non-repetitive, isotropic and high contrast speckle pattern has to be applied to a specimen in order to ensure distinction between the pixels. Next, since a (grey scale) pixel-value is not a unique signature, a so-called subset is introduced which is a small, mostly square, surface of pixels that contains a combination of speckles and represents a unique signature in the reference image (Fig. 1, a). Each subset is com-

pared between the reference state and the deformed state. The subset is shifted step by step (with a user-defined step size) and for each step the comparison between reference and deformed image is performed until the complete surface of the specimen is covered. Since the subset can change position, shape and size during the forming process, the coordinates of the material points in the deformed state are related to the coordinates of the material points in the reference state through a deformation function (the so-called shape function). This shape function is chosen as function of the expected deformation mode. For a rigid body motion, only a first order term is required for the shape function, but when an affine or irregular transformation is expected, higher order terms need to be used (Fig. 1, b).

When for example an affine transformation is expected, the relation between the coordinates of the reference coordinates (x , y) and the deformed coordinates (x' , y') can be approximated by the following shape functions:

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Fig. 1. Horizontal (U) and vertical (V) displacement fields of a specimen in uniaxial tension (a) and possible subset transformations to be fitted by the appropriate shape functions (b).

$$x' = x + u + \frac{\partial u}{\partial x} \Delta x + \frac{\partial u}{\partial y} \Delta y \quad (1)$$

and

$$y' = y + v + \frac{\partial v}{\partial x} \Delta x + \frac{\partial v}{\partial y} \Delta y \quad (2)$$

where u and v represent the translation of the centre of the subset in x and y direction respectively. The distance from the centre of the subset to the reference point (x, y) is denoted as Δx and Δy .

DIC as used in present day applications started its development in the 1980's at the University of South Carolina [2,3]. The initial single camera calculations, also called 2D-DIC, were based on the cross-correlation algorithm, which is an algorithm that is sensitive to changes in brightness of the images. In subsequent decades researchers improved the quality of the correlation results by developing more powerful correlation algorithms that are less sensitive to the offset and linear scale in illumination. A comprehensive review of the capability of different correlation algorithms was published by Pan et al. [4]. In their research, they concluded that the zero-normalised sum of squared differences (ZNSSD) or the zero-normalised cross-correlation (ZNCC) criteria offer the most robust noise-proof performance and that these algorithms are insensitive to the offset and linear scale in illumination. Besides the developments and fine-tuning of 2D-DIC, the importance of stereo correlation [5,6], a correlation technique using two cameras instead of one

rose thanks to the application of a simple and flexible calibration procedure developed by Zhang [7]. More recent research topics focus on the evaluation of the calculation accuracy and the estimation of sources of error [8–11], the matching of DIC data to finite element simulations [12] or on the implementation of a self-adapting global DIC algorithm [13]. The main advantage of the latter technique over subset-based (also termed local) DIC is that the results of the correlation are less dependent on the size of the chosen subset and thus on the experience of the user, making DIC more easily applicable for non-experts. Thanks to the initial developments, the constant improvements and the increase in the computational power of current CPUs, DIC is nowadays widely used in experimental mechanics and material science. It is one of the most applied optical measurement technologies with increasingly broad application prospects.

1.2. 2D-DIC

Most of the DIC applications use a 2D single camera setup and special care is taken to position the camera exactly perpendicular to the specimen surface. The purpose of this meticulous alignment is the reduction of out-of-plane displacements since these displacements will result in erroneous 'virtual' strains. Several solutions have been proposed to reduce the magnitude of these errors: the first is to use a telecentric lens making image magnification independent of the object distance with respect to the lens. A second solution is to place the camera as far as possible from the specimen since this distance is inversely proportional to the out-of-plane strain error. When combining a large object distance with a lens with a longer focal length, the resolution over the field of view can still be optimised. A third solution to reduce the errors originating from a non-perpendicular camera alignment is to use a second camera and perform stereo correlation. With this approach, the out-of-plane displacement will be quantified and will not be evaluated by mistake as 'virtual' strain. Of course adding a second camera and the associated calibration procedure introduce extra cost and new sources of error. It is therefore important to evaluate which of the proposed solutions yields the results with the smallest error. Relevant papers on the error estimation of a non-perpendicular camera alignment are published by Lava et al. [14] and Sutton et al. [15]. Recently Wittevrongel et al. [16] published an interesting paper on the comparison of different techniques to compensate for a non-perpendicular camera alignment. The latter includes a mechanical/experimental solution, a numerical solution based on the camera pinhole model and a method using a region of compensation that does not deform with the specimen. All three methods have proved to be successful to reduce the effects of out-of-plane motions.

1.3. Stereo DIC

The stereo correlation approach can not only be used to eliminate unwanted out-of-plane motions, but can also be used to measure surface displacements and strains in situations where (large) out-of-plane motions are unavoidable. These applications of DIC are gaining interest over the past couple of years and range from lab scale material testing such as membrane inflation [17,18], Ericksen testing [19] or drapability studies [20], to real-life military and industrial applications. Some examples of the latter are military applications such as blast loading experiments [21], the numerous DIC experiments performed by the Sandia National Laboratory (e.g. [22]), and in-situ displacement and strain measurements of thermoplastic thermoforming processes [23,24].

Some techniques allow to obtain 3D displacements using a single camera without any other optical system such as a bi-prism, mirrors or by combining DIC with fringe projection. An example of

such a technique is the use of the magnification change due to the out-of-plane displacement and the unfocusing of the object, a method that was recently published by Réthoré et al. [25]. Their approach is based on the works of Tay et al. [26] and Quan et al. [27]. In applications where very large out-of-plane displacements are to be expected however, a stereo setup still remains mandatory.

Fixed focal lenses are used in all stereo correlation applications and adjusting the lens focus during the experiments is impossible since this would jeopardise the calibration parameters of the setup. Therefore, it is of utmost importance that the target remains within the field of view and the depth of field of the cameras during the entire experiment. If the target gets out of focus, the correlation may fail leading to inaccurate results or no measurements at all. An optimal choice must be made for the position of the cameras with respect to the specimen, the focal length and the aperture setting of the lens. This is especially true in applications where retesting is not an option. The parameters affecting the depth of field and field of view are nowadays calculated based on equations from photography but do not reflect the capabilities of the correlation system.

The purpose of the present paper is to develop a procedure to define the true DOF of optical systems for large out-of-plane DIC applications. The knowledge of the correct DOF is particularly of importance when using DIC in an industrial context where the space for the camera setup is sometimes confined, the operator knowledge of DIC can be rather limited and retesting is a waste of resources. The background for this paper is the use of stereo digital image correlation (DIC) in industrial thermoforming applications but the methodology can be used for any kind of stereo DIC measurements where large out-of-plane displacements are to be expected.

The outline of this article is as follows. In Section 2 the formalisms that permit to theoretically calculate the DOF based on a photographic background are presented. Section 3 describes in detail the approach to experimentally define the true DOF for DIC applications. In Section 4, the results of the theoretical calculations and the experimental definition are compared and some critical remarks on the novel approach are formulated. We conclude in Section 5.

2. Theory: depth of field from photography

In photography various approaches have been proposed to quantify the sharpness of an image. In one of these, an image is considered in focus as long as it remains within the depth of field (DOF) of the imaging system. The DOF is defined as the range of object distances within which objects are imaged with acceptable sharpness [28]. This acceptable sharpness is a human defined parameter. The resulting expression of the DOF is a function of the lens focal length, the distance to the target and the setting of the aperture. High aperture numbers, which means that the aperture is more closed, longer distances to the target and shorter focal lens lengths, lead to higher DOF values. Vice-versa, lower aperture numbers, shorter distances and longer focal length lenses lead to smaller DOF values. Equations to calculate the DOF of an imaging system that were developed more than 50 years ago [29] are nowadays still widely used. These equations are based on the circle of confusion (CoC). In photography, the CoC diameter limit is often defined as the largest blur spot that will still be perceived by the human eye as a point. The DOF is then defined as the region where the CoC is less than the resolution of the human eye or of the display medium. A visual representation of the depth of field (DOF), the focal length (f) and the circle of confusion (CoC) is shown in Fig. 2. The object is focused at a distance s from the lens, D_n and D_f rep-

Fig. 2. Representation of the depth of field (DOF).

resent the near and far distance of acceptable sharpness respectively.

When using the abovementioned definitions, the DOF can be expressed mathematically using Equation (3):

$$DOF = D_f - D_n \quad (3)$$

with

$$D_f = \frac{s * (H - f)}{H - s} \quad (4)$$

$$D_n = \frac{s * (H - f)}{H + s - 2 * f} \quad (5)$$

where H represents the hyperfocal distance (in mm) which is mathematically defined as:

$$H = \left(\frac{f^2}{N_A * CoC} \right) + f \quad (6)$$

In Eq. (6) N_A represents the aperture number. The hyperfocal distance is the distance beyond which all objects can be brought within acceptable focus. The results are strongly dependent on the chosen CoC, which depends on the visual acuity of the person who is judging the image, the viewing conditions and possible enlargements [30]. Typical values for the CoC lie between 0.001 mm for small camera sensors to almost 0.1 mm for high resolution systems with large imaging sensors. The smaller the CoC, the more critical the definition is whether an object is within acceptable focus or not and the smaller the resulting DOF. In the current paper, an imaging system consisting of AVT Stingray F201B cameras and Pentax high resolution lenses is used. Since the CoC value of camera sensor (Sony ICX274) is not specified on the technical datasheet, the generally accepted approximated calculation using the so-called 'Zeiss' formula is used: $CoC = \text{chip diagonal (mm)} / 1730$. The chip diagonal given by the manufacturer is for this sensor 8.923 mm, leading to a CoC of 0.0052 mm. Fig. 3 shows the relation between the depth of field, the distance of the object to the camera and the aperture for such a CoC and an 8 mm (a) and a 25 mm (b) focal length lens. These graphs confirm the previously mentioned relation between focal length, target distance, aperture and depth of field. The f-number represents the aperture setting and is the ratio of the lens's focal length to the diameter of the opening through which the light travels.

Researchers performing stereo DIC measurements typically use the abovementioned equations to select an appropriate lens, to define at what distance to position the cameras and how to set the aperture. This approach is of course not bad but since it is based on a human defined value for the sharpness, it is not adapted to take into account the DIC specific capabilities. Besides, Reu showed in

Fig. 3. Theoretical depth of field as function of the distance to the camera and aperture for an 8 mm (a) and a 25 mm focal length lens (b). Notice the factor 10 difference in scaling for the vertical axis.

several publications [12,31] that images that are not perfectly in focus tend to yield better correlation results. He attributes it to the fact that the interpolation between pixels, which is necessary to get sub-pixel information, works better when there is a smooth transition in image gradients (soft edges) than with sudden transitions (sharp edges).

3. Experimental depth of field

DIC measurements generate quantitative grey scale values, while the sharpness of the human eye is a qualitative measure. Consequently, the calculations of the DOF based on sharpness, according to the equations mentioned earlier, cannot be applied as such to DIC measurements. This is especially true in setups where there is no room for errors and retesting is not an option. To find an adequate DOF value that reflects the capabilities of DIC, as function of focal length, distance to the target and the chosen aperture, a standardised testing method has been developed based on real camera and lens combinations as well as actual image correlation results.

3.1. DIC software and correlation settings

For this research the academic digital image correlation platform (MatchID V4.1 [32]) developed by the research group Mechanics of Materials, Products and Processing of the KU Leuven Technology Campus Ghent, is used. The 2D module of the software was independently benchmarked to the results of commercial systems [12] and it was found that for the bias error, MatchID is nearly identical to VIC (Correlated Solutions [33]) whereas an improved lower standard deviation by a factor of four was achieved.

The results are based on the comparison of the correlation of numerically shifted images. When comparing to Aramis (GOM [34]), similar conclusions are found for the standard deviation and also the bias error of MatchID is significantly lower.

For the stereo camera calibration in this paper, the calibration module of the MatchID software is used. The default Zhang calibration approach [7] is used and the maximum reprojection error in all cases never exceeds 0.3 pixels. The correlation settings for the displacement calculations are: a zero-normalised sum of squared differences algorithm (ZNSSD), a bicubic polynomial interpolation, an affine transformation both in 2D and stereo, a spatial correlation with updated reference and Gaussian noise handling. The ZNSSD algorithm is given by Eqs. (7) to (11):

$$C_{ZNSSD} = \sum_{i=-M}^M \sum_{j=-M}^M \left[\frac{f(x_i, y_j) - f_m}{\Delta f} - \frac{g(x'_i, y'_j) - g_m}{\Delta g} \right]^2 \quad (7)$$

with

$$\Delta f = \sqrt{\sum_{i=-M}^M \sum_{j=-M}^M [f(x_i, y_j) - f_m]^2} \quad (8)$$

$$\Delta g = \sqrt{\sum_{i=-M}^M \sum_{j=-M}^M [g(x'_i, y'_j) - g_m]^2} \quad (9)$$

$$f_m = \frac{1}{(2M+1)^2} \sum_{i=-M}^M \sum_{j=-M}^M f(x_i, y_j) \quad (10)$$

$$g_m = \frac{1}{(2M+1)^2} \sum_{i=-M}^M \sum_{j=-M}^M g(x'_i, y'_j) \quad (11)$$

The discrete functions $f(x_i, y_j)$ and $g(x'_i, y'_j)$ correspond to the reference and deformed state, respectively. The subset area is represented by $(2M+1)^2$ where M is expressed in pixels.

As to the strain calculation, the logarithmic Euler Almansi strain tensor is used (Eq. (12)), combined with a bilinear quadrilateral interpolation.

$$\epsilon^{\ln EA} = \ln(V) = \sqrt{FF^T} \quad (12)$$

In Eq. (12), V is the left deformation tensor obtained via the Cauchy-Green theorem of polar decomposition and F is the deformation gradient matrix (cf. Fig. 4).

The most optimal correlation parameters chosen in this paper are based on literature ([4,8]), as the evaluation of every single correlation parameter on the quality of the results is not part of the scope in this paper. A summary of all important correlation parameters is represented in Table 1.

In Table 1, the depth of field is calculated based on the theoretical equations from photography. Remark that even at 500 mm from the target and when using a 25 mm lens and an aperture of $f/1.4$ the DOF is barely 6 mm. The camera noise, which is evaluated at the beginning of each experiment, is the averaged standard deviation on the grey values between the region of interest of a reference image and several static images. This technique to evaluate noise is referred to as a self-correlation test [35]. Noise impacts the measurement accuracy and should be kept as low as possible. The

Fig. 4. Schematic representation of reference and deformed conventions when applying biaxial extension.

Table 1
Overview of all important correlation parameters.

Technique used	2D Digital Image Correlation
Camera brand	Allied Vision Technologies
Camera type	Stingray F201B
Lens focal length [mm]	25
Aperture (f-stop) number	f/1.4
Approximated distance to target [mm]	150 / 300 / 500
Field of view [mm]	42 × 32 / 85 × 64 / 142 × 107
Depth of field [mm]	0.4 / 1.9 / 5.6
Pixel resolution as function of FOV [px/mm]	37.5 / 18.75 / 11.2
Camera noise [%]	< 0.76
Pre-Filtering	Gaussian – Kernel 5
Subset [px*px]	58
Step [px]	9
Correlation criterion	ZNSSD
Shape function	Affine
Interpolation function	Bicubic polynomial
Correlation threshold	0.9
Progress history	Spatial + update reference
Number of measurement points	19965
Total number of images	Various
Displacement	
Spatial resolution [px]	58
In-plane resolution [mm]	0.0048 (300 mm)
Strain	
Smoothing method	Bilinear quadrilateral
Strain tensor	Logarithmic Euler-Almansi
Strain window [px]	15
Virtual strain gauge [px]	127
Spatial resolution [px]	184
Resolution [μm/m]	43 (300 mm)

average noise values in all experiments in this paper are below 0.76%. Up to 1% standard deviation on grey values is usually acceptable when using decent image acquisition hardware. An interesting paper on the impact of noise is published by Wang et al. [9]. The definition of the resolution specified in Table 1 is the smallest change in a quantity being measured that causes a perceptible change in the corresponding indication [36]. In DIC, the displacement resolution is defined by the level of noise (camera and surrounding) and can be quantified by performing a self-correlation test and calculating the displacement, which should normally be zero. The resolution of the displacement is then defined as the standard deviation on this zero displacement [13]. The same approach is adopted for the strain resolution in Table 1. Spatial resolution is defined as the shortest distance between two spatially independent measurements. For displacements this is the subset size. Smaller

subset sizes increase the spatial resolution but decrease the resolution since the standard deviation will increase [37]. Since strains are derived from displacements, the spatial resolution of strain is dependent of the subset size (SS), the step size (ST) and the strain window (SW) that is adopted to smoothen the displacements and reduce displacement noise. All parameters are expressed in pixels. Spatial resolution of strain (SRS) can be calculated as [38]:

$$SRS = [(SW - 1) * ST] + SS \quad (13)$$

Another often used term to compare strain from DIC to strain gauge measurements, is the virtual strain gauge (VSG) [39]. The VSG is a term derived from finite element analysis. In FEA software it is quite easy to compare strain gauge measurements to simulation results since the average strain from the surface mesh below the gauge can be used. In DIC a similar approach can be adopted. The size of the virtual strain gauge (VSG, expressed in pixels) can be written as [38]:

$$VSG = [(SW - 1) * ST] + 1 \quad (14)$$

3.2. Focus definition

In order to guarantee that the images used in this research are in focus, a so-called focus measure operator is used [40]. A focus measure operator (FM) is an algorithm that is used to measure the focus level of every pixel of an image. These operators are widely used in autofocus applications or for shape-from-focus analyses. A nice review and comparison of the different operators that can be used for shape-from-focus measurements is available in [40]. The usability of a number of focus measure operators from the latter publication on printed speckle pattern used in DIC applications is investigated in this paper. The operators are listed in Table 2.

To find which focus operator is the best in recognising a well-focused image, three experiments are targeted. The first experiment (1) consists of evaluating the FM value of a sequence of virtually generated speckle images with different speckle sizes. Good focus measures are those that are unaffected by the speckle size or that show a clear and unambiguous difference in focus value between the different speckle sizes. The second experiment intends to evaluate the robustness of the FM when the target is moving away from the camera. This experiment consists of two parts. The first part (2a) is the evaluation of images taken of a fixed speckle pattern moving backwards perpendicular to the lens while each time manually refocusing the lens, the second part (2b) is similar but without focusing after each displacement. Good focus measures should be

Table 2
Focus measure operators and references.

Operator	Operator family	Reference in [40]
DCT energy ratio (DCTE)	Discrete cosine transform operator	DCT1
DCT reduced energy ratio (DCTR)	Discrete cosine transform operator	DCT2
Grey-level variance (GLVA)	Statistics-based operator	STA3
Grey-level local variance (GLLV)	Statistics-based operator	STA4
Variance of Laplacian (LAPV)	Laplacian-based operator	LAP4
Tenengrad (TENG)	Gradient-based operator	GRA6
Tenengrad variance (TENV)	Gradient-based operator	GRA7
Image contracts (CONT)	Miscellaneous operator	MIS3

almost insensitive to the displacement of focused images (part one of the experiment) and should show a clear drop in focus measure for the images that are not refocused (part two of the experiment). The third experiment consists of evaluating the FM value for images of a fixed speckle pattern at a fixed distance while changing the setting of the focus. For this last experiment, the best FM operator is the one that clearly shows differentiation between focused and unfocused images. Overall, the best FM operator for the evaluation of the focus of speckle patterns is the one that scores best on all three experiments.

Results from the first experiment are displayed in Fig. 5. The chosen speckle diameters range from 0.5 to 5.5 mm in steps of 0.5 mm using the same speckle density. The focus values of each operator are normalised relative to the maximum value of that operator. Comparing absolute values of the operators makes no sense because the calculation methods are different. From the figure it is clear that when changing the speckle density (by increasing the size of the speckles as is the case in this example), the relative sharpness will drop in most cases. This is not the case for the GLLV, DCTE and DCTR operators that perform the worst in this test. The best performing is the GLVA operator since the speckle size is not significantly affecting the focus value.

In the second experiment, a fixed speckle pattern is chosen and positioned at 300 mm from the lens, and subsequently it is moved backwards perpendicular to the lens. After each step, initially every millimetre but after 5 mm in increasing steps to a final distance of 650 mm, the lens is manually refocused. The normalised focus values are plotted as function of the distance to the lens in Fig. 6. The best operator is the one that stays as close as possible to the maximum value. It can be seen that the GLLV, TENV and LAPV operators perform worse than the other operators in this test.

The same experiment is repeated but without refocusing between two consecutive images. The step between two images is also kept each time to 1 mm. Results are displayed in Fig. 7. The first image (distance from starting point = 0) in this case provides the highest focus value. The focus value decreases with increasing distance, as expected since the images become unfocused. From this experiment it is difficult to judge which one is better since all focus values decrease with increasing distance. Nevertheless, some normalised focus values decrease faster than others (i.e. TENV, LAPV, GLLV and TENG) meaning they are more sensitive to changes in focus and are thus more suitable for stable and unambiguous differentiation of well-focused images.

The third and last experiment consists of calculating the focus value for a speckle pattern at a fixed distance while manually changing the focus setting. The peak in Fig. 8 represents the opti-

Fig. 5. Normalised focus value for different focus operators as function of the speckle size/density.

Fig. 6. Normalised focus value as function of the distance to the lens for a fixed speckle pattern at 300 mm starting distance while refocusing.

Fig. 7. Normalised focus value as function of the distance to the lens for a fixed speckle pattern at 300 mm starting distance without refocusing.

Fig. 8. Focus value for a fixed pattern at a fixed distance but with changing focus setting.

mal focus value. All operators clearly distinguish image number 16 as best in focus. This is also the image that was visually (trial group of 10 persons) assessed as the most in focus. In this test, the preference is given to the focus operator that leads to a curve with the narrowest peak (TENV) because that operator leads to the most unambiguous differentiation between focused and unfocused images.

When an operator is used to evaluate the sharpness of an image, it should detect as accurately as possible the most focused image in

a series. Besides, it should present a stable value when a sample is moved away from and to the camera. Finally, the sensitivity on speckle size and distribution should be straight forward. To quantitatively evaluate the performance of the operators, in Table 3 points are given to the four operators that perform the best on each experiment (1 being the top performing operator and 4 the fourth best). The other operators get 6 points, the extra point is considered as a penalising coefficient. From this comparison, the preferred FM operator is the ‘Tenengrad’ (TENG) focus measure operator from Krotkov [41]. It scores slightly better than the TENV and LAPV focus operators and is, unlike any other, in all tests within the top four performing operators. The Tenengrad operator convolves an image in X and Y direction using the Sobel operators to get image gradients (G_x , G_y) and then calculates the focus value as a sum of squares of the gradients in both directions (Equation (15)).

$$FM_{Tenengrad} = \sum_i \sum_j (G_x(i, j)^2 + G_y(i, j)^2) \quad (15)$$

The Tenengrad operator is used in the remainder of this paper in all cases where the level of focus needed to be evaluated.

3.3. Calculating depth of field using a single camera

A dedicated laboratory setup is developed consisting of a single camera (AVT Stingray F201B) equipped with a 25 mm fixed focal length lens with aperture settings between f/1.4 and f/16. A 100×100 mm flat sample with a laser printed randomly generated digital dot pattern (0.78 mm dot diameter) is prepared and positioned on a linear guide at a distance of 150 mm perpendicular to the lens and centered in the optical axis of the camera. In this particular setup, the dot size corresponds to a diameter of 29 pixels. This is vastly larger than the minimum 3×3 pixels which is a commonly adopted rule of thumb to ensure accurate matching and reasonable intensity pattern reconstruction via interpolation without aliasing [1,42,43]. The reason for choosing this speckle size is that artificial compressions up to 130% are expected in this test. The safety margin is taken proportional to this value. The comparison of the printed dot pattern used for this study to the more common spray-painted patterns was discussed in a previous publication [44].

In a first step, a reference image of a focused dot-printed target is taken at the starting distance of 150 mm using the smallest possible aperture (f/1.4) since this corresponds with the smallest depth of field, making focusing easier. After the focused reference image is taken, the sample is moved 1 mm backwards on the linear guide, the lens is refocused and another image is taken. This procedure is repeated in steps of 1 mm for the first 5 mm and then in increasing step sizes until 350 mm from the starting distance. The consecutive images are correlated spatially using the previous image as the reference (also referred to as with updated reference or incremental) in MatchID2D. The calculated average artificial strain values and

Table 3
Overview of results from focus operator experiments.

Operator/Experiment	1	2a	2b	3	Total
DCTE	6	4	6	6	22
DCTR	6	3	6	6	21
GLVA	1	6	6	6	19
GLLV	6	6	3	3	18
LAPV	4	6	2	2	14
TENG	3	1	4	4	12
TENV	6	6	1	1	14
CONT	2	2	6	6	16

their corresponding standard deviations over the region of interest, which are in a 2D setup based solely on the backward movement of the plate and the resulting reduction of the speckle size, are plotted in a chart relative to the distance from the camera (Fig. 9). The same procedure is repeated for two other starting distances, i.e. 300 mm and 500 mm with respective dot diameters of 1.56 mm and 2.6 mm, maintaining always the same dot diameter in pixels, making the results independent from the speckle, subset and step size. The artificial strain is used as the correlation quality parameter, since other parameters, such as the average correlation coefficient (R), cannot be used as a qualitative comparison between speckle patterns since it is too much affected by lighting, speckle size, subset size and step size. The correlation coefficient is a measure of the quality of a correlation and the purpose of correlation software is to maximise this coefficient, or to minimise the correlation criterion: $C = 1 - R$ (cf. Eq. (7)). Moreover, the correlation coefficient when using updated references, which is the case here, gives an indication of the correlation capabilities between two consecutive images but is meaningless when evaluating the correlation quality of the deformed versus the reference image.

The experimental procedure as described above is executed and the resulting raw data from 2D correlation is exported and loaded in an automated custom-made Matlab script. The script extracts the resulting average, minimal, maximal and standard deviation of the maximum principal strain values for every image. Fig. 9 expresses these values for a focused target moving away from the camera at three different starting distances relative to the distance from the starting point. For the sake of completeness: the effect of a smaller or larger subset and step size as well as the strain window size has been assessed. Differences were found in the absolute strain magnitude but the relative results were comparable to those of Fig. 9.

Next, a third order polynomial regression function is fitted to the average strain values for each starting distance. This function is needed for further calculations, providing interpolated maximum principal strain values on a millimetre scale.

In a next step, the same experimental procedure is repeated without focusing after each displacement. This experiment is repeated for the combination of different aperture settings (f/1.4, f/2, f/4 and f/8) and for the different starting distances (150, 300 and 500 mm). Once all unfocused images are acquired, they are correlated using MatchID2D (spatial correlation with updated references) and the resulting exported raw data is loaded in the auto-

Fig. 9. Virtual strain values as function of the distance between the camera and the target for an AVT Stingray F201B camera with a 25 mm focal length lens at three different starting distances (150, 300 and 500 mm) and an aperture setting of 1.4.

mated script. The script calculates the average maximum principal strain from the imported results and plots the data as function of the distance from the starting point. Next, it calculates a cut-off point for the achievable depth of field by comparing the third order polynomial regressed data of the average strain plot of the focused images to the average strain values of the unfocused images. The DOF cut-off point (threshold) is based on a deviation from the average fitted function (i.e. 5%) or on an excessive standard deviation (i.e. twice that of the focused images) of the strain values, depending on which one is exceeded first. These arbitrary values can be modified depending on how much deviation is tolerated on the correlation results. The procedure as described above can be seen as a camera/lens characterisation procedure that needs to be executed only once for every camera and lens combination.

When repeating the experiment for different starting distances and aperture settings, this procedure results in the complete working range in terms of depth of field as function of distance and aperture for a specific camera and lens combination. A typical resulting graph for the setup as described earlier with a 25 mm focal length lens is presented in Fig. 10. The results for an aperture $f/16$ are omitted since the brightness of the images in that case was insufficient. Remark that the DOF values in this figure are significantly higher than those mentioned in Table 1 or Fig. 3(b) based on the theoretical calculations.

Besides the characterisation of a camera and lens combination, a graphical user interface is added to run the developed script. This addition makes the approach industrially more applicable, as originally intended. This user interface also allows to calculate the field of view as function of the distance to the target, when chip size, resolution and lens focal length are given. When the dimensions of the product to be deformed are also given (length, width and height ($\approx$ wanted DOF)), the software provides the user with a minimum distance for positioning of the cameras to see the complete FOV. It also advises on the setting of the aperture to have sufficient sharpness during the complete deformation, based on the characterisation measurements. The software program will always suggest the closest possible location to position the cameras to provide the user with the highest possible resolution. When, due to mounting restrictions, the cameras cannot be installed at the proposed distance, the user can manually select a different distance and the software will display the FOV, resolution and DOF at the chosen distance. The program also calculates the appropriate diameter of the speckles to be printed for that specific setup (camera, lens, distance) and it generates a corresponding random speckle pattern with the appropriate speckle size. The developed graphical user interface and

Fig. 10. Experimental depth of field as function of the distance to the camera and aperture for an AVT Stingray F201B camera with a 25 mm focal length lens and a printed 29 pixels/dot speckle pattern.

the script are available on the Matlab file exchange website (<http://www.mathworks.com/matlabcentral/fileexchange/>). The diagram in Fig. 11 schematises the complete procedure.

4. Discussion and remarks

In the opinion of the authors, this novel approach gives more reliable results than the approach based on the theoretical calculations and the CoC since it is based on real camera and lens combinations, real speckle patterns and correlation results. The approach even includes the effect of the chosen correlation criteria and the performance of the DIC software. When subtracting the DOF values from the theoretical calculations (Fig. 3, b) from the DOF values of the experimental approach (Fig. 10) it can be seen that the achievable DOF for DIC applications is larger than what theoretical calculations predict (Fig. 12). In other words, this is a validation/confirmation of the finding of Reu [31] that correlation images do not need to be perfectly in focus to yield good correlation results. Besides, this makes it possible to place the cameras closer to the target (when the FOV allows this). As a consequence, this means a direct gain in resolution without having to use higher resolution, and thus more expensive, cameras.

Two critical remarks have to be made on the abovementioned approach. In order to rely on the data from the novel approach, care has to be taken to use the same correlation settings as used during the camera and lens characterisation (speckle, subset, step, strain window and correlation settings). Digitally or screen-printed speckles of the correct size and distribution are therefore advised. A second remark is that it is assumed that the results from the 2D-DIC setup can be interpolated to a stereo setup. The latter is plausible when a good stereo calibration is performed, since stereo correlation consists of two 2D correlations combined by triangulation and cross-camera matching.

5. Conclusions

Stereo correlation accuracy in large out-of-plane application is affected by the level of focus of the correlation images. Nowadays researchers rely on their experience or on simple equations from photography to define the position of the cameras, to select an appropriate lens and to choose the aperture setting that results in the target remaining in focus during the deformation experiment. Often a vast safety margin on the distance is chosen or a number of trial runs are executed to find the correct combination. When a safety margin is chosen for the distance of the camera with respect to the target, this directly affects the correlation resolution and accuracy. In applications where resolution and accuracy are critical or where there is no possibility to use trial and error due to the availability of the material or the cost of the setup, the previous approach cannot be followed. The methodology presented here enables to characterise a relevant depth of field window for a specific camera/lens combination as function of the distance to the target and the aperture setting. The approach is based on actual correlation results and proves to yield depth of field ranges that are less strict than the ones based on theoretical calculations. This makes it possible to position the cameras closer to the target, leading to an improved resolution and correlation accuracy without the cost of higher resolution cameras and lenses.

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Fig. 11. Procedure for the definition of the depth of field of stereo cameras based on 2D-DIC measurements.

relation platform MatchID and Gerard Palome Bartrina for the development of the testing rig.

Fig. 12. Theoretical depth of field subtracted from the experimental depth of field as function of the distance to the camera and aperture for an AVT Stingray F201B camera with a 25 mm focal length lens.

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