The Effect of Bit Depth on High Temperature Digital Image Correlation Measurements

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THE EFFECT OF BIT DEPTH ON HIGH TEMPERATURE DIGITAL IMAGE CORRELATION MEASUREMENTS

by

Steven Robert Jarrett

A thesis submitted in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

in

Mechanical Engineering

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ABSTRACT

The Effect of Bit Depth on High Temperature Digital Image Correlation Measurements

by

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Utah State University, 2021

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Digital Image Correlation (DIC) is a camera-based method of measuring displacement and strain. High-temperature DIC is challenging due to light emitted from the sample which can saturate the camera sensor. Blue-DIC and UV-DIC have been developed to minimize this effect, but the maximum sample temperature range of DIC remains a function of the camera and camera settings. Bit depth, also referred to as color depth or number of bits, is an important camera setting which affects the dynamic range of an image, but which has received insufficient attention in DIC literature. In this work, the effect of bit depth on DIC measurements is investigated both analytically and experimentally. Relationships involving DIC displacement uncertainty, image noise, image averaging, and the effective number of bits are derived and discussed. Blue-DIC is performed on images taken at varying exposure times, bit depths, numbers of images averaged, and temperatures up to 1600 °C. If image noise is sufficiently low, increasing bit depth reduces DIC random error. The effective number of bits ($B_{eff}$) metric is presented and discussed as an indicator of the appropriate number of bits to use for image capture and storage. Spatial distribution of noise and implications of using a color camera are discussed. Using increased bit depth and reduced exposure time, the maximum sample temperature for DIC measurements was shown to increase without negative impact on measurement precision.

(71 pages)
Digital Image Correlation (DIC) is a camera-based method of measuring mechanical displacement and strain which is commonly used in high-temperature experiments due to its ability to take contactless measurements. High-temperature DIC is challenging due to light emitted from the sample which can saturate the camera sensor. Blue-DIC and UV-DIC have been developed to minimize this effect, but the maximum sample temperature range of DIC remains a function of the camera and camera settings. Bit depth, also referred to as color depth or number of bits, is an important camera setting which affects the dynamic range of an image, but which has received insufficient attention in DIC literature. In this work, the effect of bit depth on DIC measurements is investigated both analytically and experimentally. If image noise is sufficiently low, increasing bit depth reduces DIC random error. Using increased bit depth and reduced exposure time, the maximum sample temperature for DIC measurements was shown to increase without negative impact on measurement precision.
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Steven Jarrett
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I. INTRODUCTION

Digital Image Correlation (DIC) is a camera-based method of measuring displacement and strain. Since its first practical application in the 1980s [1], popularity of the technique in peer-reviewed literature has grown exponentially while other popular strain-measurement methods have not seen a significant increase in use [2]. One area of current research is in increasing the range of sample temperatures for which DIC can be used. The purpose of this work is to explore the effect of a camera’s bit depth, also referred to as color depth or number of bits, on the resulting DIC measurement in an effort to increase this range of temperatures. The following sub-sections will introduce the DIC measurement, the challenges associated with high-temperature DIC, prior work related to bit depth and noise, and the proposed research.

I.1. What is DIC?

Digital Image Correlation (DIC) is a camera-based, full-field, non-contacting method of measuring displacement. In practice, DIC begins with preparing a test procedure with minor modifications: the specimen is given a high contrast pattern, typically a painted speckle; and one or more cameras are positioned to view the sample during testing. Images of the specimen are taken before, during, and after the test. These images are then analyzed using DIC software to find displacement, strain, and sometimes velocity of the pattern between images [3].

Because DIC is non-contacting, provides full-field data, and has a low cost per test, it is used in a wide variety of testing circumstances. These applications span many industries; for example, nuclear [4], automotive [5,6], medical [7], and defense [8]. The technique’s versatility has allowed it to be used with extremes such as measurements at the nanometer-scale [9] and tens-of-meters-scale [10,11], testing of 3000 °C samples [12], and applications requiring IR [13] or UV [14,15] imaging. DIC is versatile and widely used, but properly using the technique requires an understanding of its basic limitations and working principles.

I.2. How does the DIC algorithm work?

DIC uses an image correlation algorithm to calculate displacements. After the images are taken, the algorithm begins by dividing the first, or reference, image into regions called subsets. The algorithm then searches for each subset in subsequent images by varying a parameter vector \( \vec{p} \) (which includes
information such as displacement and rotation) to minimize some variation of the sum of squared differences (SSD) criterion [16], shown in Eq. (1):

\[ \chi^2 = \sum |I'(\xi(\bar{x}, \bar{p})) - I(\bar{x})|^2 \]  

(1)

Where:
\[ \chi^2 = \text{correlation coefficient} \]

\[ I(\bar{x}) = \text{a pixel in the reference image at location } \bar{x} \]

\[ I'(\bar{x}) = \text{a pixel in the current image at location } \bar{x} \]

\[ \xi(\bar{x}, \bar{p}) = \text{some transformation of } \bar{x} \text{ using parameter vector } \bar{p} \]

Although variations of the cross correlation (CC) algorithm can also be used [17], which is common for fluid measurements in particle image velocimetry (PIV), the SSD algorithm is more efficient [16] and is generally more popular for solid mechanics. During the search, the algorithm makes a series of methodical guesses (\( \bar{p} \)) for where the subset from the first image could be in the second. The guess which minimizes Eq. (1) is the location of the subset in the new image. Once the algorithm has determined the location of all subsets in the new image, it then calculates relative displacement, strain, velocity, and any other quantity of interest between the two images.

Researchers and developers have made many improvements to DIC. Some improvements to the algorithm include:

- using a normalized sum of squared differences (NSSD) or zero-normalized sum of squared differences (ZNSSD) correlation criterion, which account for changes in overall subset brightness [16];
- using a shape function (\( \xi \)) to allow correlation using complex subset transformations [16,18,19];
- using advanced interpolation methods such as cubic B-spline to capture sub-pixel movement [16,17];
- low-pass filtering the images to reduce image noise (which can in turn reduce interpolation error) [16,20];
- and applying a pixel weighting function to place greater value on correlation at the center of the subset [16].
In addition to improvements on the fundamental correlation algorithm, several types of DIC have been developed. Some types of DIC include:

- **2D-DIC**, which requires only one camera and is limited to measuring in-plane motion of planar surfaces [16,21];

- **3D- or Stereo-DIC**, which uses two or more cameras to obtain 3-dimensional displacements and strains on arbitrarily shaped surfaces [16,22];

- **Volumetric DIC**, which extends the idea of 3D-DIC to allow tracking of particles within a 3D volume [16,23];

- **Real-time DIC**, which performs DIC on a reduced number of subsets in real time and can be used for feedback-control loops [24,25].

- **Global DIC**, which uses mesh-based methods inspired by finite element analysis (FEA) to track the entire region of interest simultaneously rather than by dividing it into subsets [26].

In order to obtain a high quality DIC measurement, several conditions must be met. The sample must have a high quality speckle pattern [27] – a random pattern with appropriately sized speckles [28,29], sufficient contrast [21,30,31], soft-edged speckles [32], and good speckle density [33]. The sample also must have appropriate lighting [21,34]. Good speckles and lighting affect factors like spatial resolution [29], DIC accuracy [28], and DIC noise [30]. Camera optics must have sufficiently low distortion, which can cause artificial strain gradients if present and not calibrated for [35]. For 2D-DIC, the object must be planar, the object plane must be parallel to the camera sensor plane, and the object must not undergo out-of-plane motion or deformation [16] since any of these conditions will produce displacement inaccuracies and false strain gradients. Other factors can also be important for DIC depending on the test to be performed; a more complete discussion of these can be found in the International Digital Image Correlation Society’s (iDICs) Good Practices Guide [36] or in Phil Reu’s series “The Art and Application of DIC” [1]. Methods for meeting these conditions are well established under normal circumstances, but doing so in extreme environments can be difficult.
I.3. High-temperature DIC

Although DIC is non-contacting and thus is well suited to extreme environments, performing DIC on high-temperature samples can be challenging due to light emitted from the sample. As sample temperature increases, the intensity and frequency of light emitted from the sample increase according to Planck’s law [37]. Because images of the sample include both reflected and emitted light, then as sample temperature increases, the increased emitted light brightens the image and can eventually saturate the camera sensor. At lower temperatures, this is not a problem because emitted light is not a significant portion of the light collected by the sensor. In 1996, Lyons et al demonstrated DIC to be capable of measuring samples at temperatures up to 650 °C [38].

One solution to the background radiation problem is to use a blue (~450 nm) light source and bandpass optical filter. In 2009, Grant et al showed that using blue-light illumination and optical filtering could extend the maximum temperature of DIC measurements to at least 1000 °C [39]. Two years later, this was extended to 1500 °C by Novak and Zok [40] and has been used in several other high-temperature experiments [12,41–46]. Most recently, the temperature limit of blue-DIC has been extended to 3067 °C by Pan et al [12]. In their work, the authors utilized the difference in the spectral emissivity of Tantalum Carbide and Tungsten to create a speckle pattern that would work at any temperature. As the temperature increased, however, the authors were forced to change the lighting conditions and exposure time, which increases DIC measurement uncertainty [12,47].

The idea of using an optical filter has also been extended into the UV spectrum. In 2014, Berke and Lambros took the idea of filtering further by using ultraviolet (UV) lighting and a UV bandpass filter to further reduce background radiation from the sample in 2D-DIC images [15]. This idea was demonstrated successfully with 3D UV-DIC by Dong et al in 2019 [48]. Other variations of UV-DIC include ultraviolet diffraction-assisted image correlation (UV-DAIC) for taking 3D measurements with a single camera [22] and high-magnification UV-DIC at long working distances [14]. In spite of the use of optical filters, however, DIC images still suffer from offsets in lighting at extreme temperatures, requiring the user to balance the risk of over-exposure with the risk of not having enough contrast for effective DIC measurement [21]. This might be mitigated by continuing to shorten the wavelength of the light source and filter, but doing so increases the radiation health risk to the user.
Because it is impossible to filter out all thermal radiation from high-temperature specimens, the maximum measurable temperature of DIC also depends on the camera and camera settings. In an effort to quantify the relationship between camera settings and maximum temperature, Thai et al correlated images of a high-temperature specimen taken at multiple temperatures and exposure times and analyzed the resulting DIC uncertainty [21]. In his work, Thai pointed out that increases in sample temperature tend to produce offsets in sample lighting whereas changes in camera sensitivity (such as exposure time) produce linear scaling in lighting. His article concludes by suggesting a normalized metric, $\Delta$, representing the range of the median 90% of all pixel values which should be minimized but kept above a minimum of 50 (for an 8-bit camera) for effective DIC measurements at high temperatures:

$$\Delta = Z_2 - Z_1$$

Where $Z_1$ and $Z_2$ are the intensity values at which the cumulative distribution function of the image equals 0.05 and 0.95, respectively, as shown in Figure 1.

Figure 1: Example image and histogram with $Z_1$, $Z_2$, and $\Delta$ shown.

Thai’s suggestion builds on similar suggestions made by Phil Reu [34], that the difference in intensity between ‘typical’ bright and dark pixels should be at least 50 grayscale values (counts), and by the International Digital Image Correlation Society (iDICs) [36], that the contrast should be at least 20% (50 counts between light and dark features for an 8-bit camera).
1.4. How does bit depth affect DIC?

Bit depth refers to the number of bits used to store a digital value. When light is recorded by a camera sensor, it is converted to a digital, discrete value represented using a number of bits. The maximum number of distinct values storable by an $B$-bit number is $2^B$. When the number of bits is changed, the number representing the amount of light incident on a pixel typically scales with the maximum value ($2^B - 1$) even though the amount of light doesn’t change. This conversion to a discrete value inherently introduces noise [49].

Reducing image noise reduces DIC uncertainty. In 2009, Wang et al [31] derived a simple expression showing the relationship between three quantities: camera noise, the sum of squared differences between two adjacent subsets, and the variance of a DIC displacement measurement. In one dimension, this relationship is given by Eq. (3):

$$\sigma_{DIC}^2 \approx \frac{2\sigma_{img}^2}{\sum_{i=1}^{SS} \sum_{j=1}^{SS} I^*_x(i,j)^2}$$

(3)

Where:

- $\sigma_{DIC}^2 =$ variance of DIC displacement [pixels$^2$]
- $\sigma_{img}^2 =$ variance of pixel intensity, or image noise [counts$^2$]
- $SS =$ the width of a square (SS x SS) subset (I$'$) [pixels]
- $I^*(i,j) =$ the subset to be correlated, with i and j denoting a specific pixel in $I^*$
- $I^*_x(i,j) = \frac{d}{dx}(I^*(i,j))$, where x is the direction of interest

This local, subset-specific estimate of DIC uncertainty was adjusted by Pan et al [50] using the Mean Intensity Gradient (MIG), given in Eq. (4), to estimate DIC uncertainty across an entire image based on a given subset size:

$$\sqrt{\sum_{i=1}^{SS} \sum_{j=1}^{SS} I^*_x(i,j)^2} \approx SS \cdot MIG$$

(4)

Where:

$$MIG = \frac{1}{WH} \sum_{i=1}^{W} \sum_{j=1}^{H} \sqrt{I_x(i,j)^2 + I_y(i,j)^2}$$

(5)
And:

\[ I_x, I_y = \text{partial derivatives of the image in the horizontal and vertical directions, respectively} \]

\[ W, H = \text{width and height of the image, respectively [pixels]} \]

It should be noted that the derivatives of I are summed over the whole image in Eq. (5), whereas the derivatives of I* are summed over subsets in Equations (3) and (4).

Inspection of Equations (3)-(5) suggests DIC uncertainty can be decreased by decreasing camera noise \( \sigma_{img}^2 \), increasing the subset size (SS), or increasing the contrast between neighboring pixels (MIG). Increasing the subset size is trivial in difficulty but comes at the expense of spatial resolution. Increasing MIG can be done by improving the speckle pattern or lighting. This is straightforward under normal conditions, but doing so at high temperature [21] or high speed [51] may not be feasible if a sufficiently strong light source is not available, practical, or safe. It becomes appealing in such cases to explore the feasibility of reducing camera noise as an alternative.

Perhaps the most straightforward way to reduce noise is to purchase a camera or set of cameras with a low level of noise. If a better camera cannot be procured, some recommendations exist to minimize noise such as by increasing lighting rather than increasing gain [30] or by averaging images [30,52,53]. Because bit depth affects the dynamic range of a measurement, it stands to reason that increasing bit depth may be another simple way to decrease DIC uncertainty. This topic has yet to be explored in DIC literature.

I.5. What does this work contribute?

The purpose of this work is to explore the effect of bit depth on both the random error and maximum sample temperature of DIC. It is anticipated that increasing bit depth will decrease DIC uncertainty and increase the measurable sample temperature range. The remainder of this document provides necessary theoretical discussion, documents methods used, and presents and discusses the results from the study.
II. THEORY

To establish a solid theoretical foundation for the analysis of the effect of bit depth on DIC measurement uncertainty, it is necessary to derive a few quantitative relationships as applied to DIC. The following sub-sections establish equations relating DIC uncertainty to image uncertainty, explore the effect of image averaging, and derive the effective number of bits ($B_{eff}$) metric for image-based measurements.

II.1. Derivation of the relationship between DIC displacement variance and bit depth

Drawing upon prior work, it is possible to derive an analytical relationship between bit depth and DIC displacement uncertainty beginning with image noise. Image noise ($\sigma_{img}^2$) can be expressed as the sum of many smaller contributors, each representing a step in the conversion from an image incident on the sensor to the camera’s digital output, as shown in Eq. (6). Note it is assumed that noise (normally calculated using mean-squared error) is equal to variance, which is true if the noise has zero bias [54].

$$\sigma_{img}^2 = \sigma_Q^2 + \sum \sigma_i^2$$  \hspace{1cm} (6)

Where:
- $\sigma_{img}^2 = \text{pixel intensity noise (variance)}$
- $\sigma_Q^2 = \text{quantization noise}$
- $\sigma_i^2 = \text{all other sources of noise in the system}$

Quantization noise is calculated by representing the error between the quantized value and the true value as a random variable with uniform probability distribution [49] on the interval [-0.5,0.5). The variance [55], then, is given by Eq. (7):

$$\sigma_Q^2 = \frac{(b - a)^2}{12} = \frac{1}{12}$$  \hspace{1cm} (7)

Where:
- $\sigma_Q^2 = \text{variance of the pixel value due to quantization}$
- $a,b = -0.5,0.5$ (lower and upper bounds of quantization error, respectively)

For further elaboration on the source of the 1/12 term, the reader is encouraged to work through Eq. (5.4.4) of [55] (in brief, an equation on the order of $\left(\frac{x^2}{2}\right)$ is integrated creating a 1/24 term, and the
specific function and the bounds of integration cause a 2x multiplier as well). Equation (7) shows quantization noise is constant regardless of bit depth, camera, temperature, or any other variable. In contrast, noise sources which occur prior to quantization scale with \((2^B - 1)\). Noise sources which occur after quantization are neglected for this derivation. Substituting Eq. (7) into Eq. (6), the total image noise becomes:

\[
\sigma_{\text{img}}^2 = \frac{1}{12} + \sum_i \sigma_i^2
\]  

(8)

Combining Equations (3), (4), and (8) and assuming zero noise bias yields Eq. (10), a relationship between DIC variance, image noise (divided into quantization noise and noise from other sources), subset size, and the MIG of the image.

\[
\sigma_{\text{DIC}}^2 \approx \frac{2\sigma_{\text{img}}^2}{SS^2 \sum_{i=1}^{SS} \sum_{j=1}^{SS} I_x(i,j)^2}
\]

\[
\approx \frac{2\sigma_{\text{img}}^2}{SS^2 (MIG)^2}
\]

\[
\approx 2 \left( \frac{\frac{1}{12} + \sum \sigma_i^2}{SS^2 (MIG)^2} \right)
\]

(9)

Where:

\[
\sigma_{\text{DIC}}^2 = \text{variance of DIC displacement [pixels]}
\]

\[
\sigma_{\text{img}}^2 = \text{image noise}
\]

\[
\sigma_Q^2 = \frac{1}{12}, \text{quantization noise}
\]

\[
\sum \sigma_i^2 = \text{noise from other sources}
\]

\[
SS = \text{subset size}
\]

\[
MIG = \text{mean intensity gradient}
\]

Note that \(\sigma_i\) and MIG, are both dependent on the camera/image and thus will scale with \((2^B - 1)\). As such, an increase in bit depth will increase both terms by the same factor. In contrast, the quantization noise term is constant, so an increase in bit depth will increase the denominator in Eq. (9) faster than the numerator, resulting in an overall decrease in DIC variance. Thus, increasing bit depth reduces DIC uncertainty. Although this will always be true mathematically, the reduction is expected to be significant.
only if the noise from other sources is of similar or smaller magnitude than the noise due to quantization ($\sum \sigma_i^2 \leq 1/12$). Because the amount of image noise is critical to the relationship between DIC uncertainty and bit depth, it is desirable to consider ways to control image noise.

II.2. Controlling image noise using the image averaging method

One way to control image noise is using image averaging. Image averaging is a common method used for static or quasi-static tests when removing image noise [30,53] or thermal distortion [52] is necessary. The method is founded upon the principle of taking multiple measurements to reduce uncertainty of the mean of a random variable. For a continuous random variable (X), Eq. (11) is the variance of the mean ($\sigma_{\bar{X}}^2$) of $N_{avg}$ samples of X [54].

$$\sigma_{\bar{X}}^2 = \frac{\sigma_X^2}{N_{avg}}$$  \hspace{1cm} (11)

Where:

- $X = \text{an arbitrary continuous random variable}$
- $\bar{X} = \text{mean of } X$
- $\sigma_X^2 = \text{variance of } X$
- $\sigma_{\bar{X}}^2 = \text{variance of the mean of } X$

$N_{avg} = \text{number of samples used to calculate } \bar{X}$

Thus, the noise in an averaged image ($\sigma_{img}^2$) is reduced by a factor of $N_{avg}$ compared to a non-averaged image. Note, however, if the images are converted back to integer values prior to performing DIC, doing so introduces additional quantization noise. Thus, for an integer-valued averaged image, the expected image noise ($\sigma_{img,exp}^2$) in an averaged image is given by Eq. (12).

$$\sigma_{img,exp}^2 = \frac{1}{12} + \frac{\sigma_{img}^2}{N_{avg}}$$  \hspace{1cm} (12)

Note that Eq. (12) should only be used if $N_{avg} > 1$ because when $N_{avg} = 1$ the image is already integer-valued. To verify this relationship, a numerical study was performed to determine the proper way to calculate image noise and the effect of image averaging; this study is included in the Appendix.
Having established the effect of image averaging on image noise, the effect of image averaging on expected DIC uncertainty can also be derived. Incorporating Eq. (11) into Eq. (9) results in Eq. (13), the expected DIC displacement uncertainty due to image noise for averaged images.

$$\sigma_{DIC, exp}^2 \approx \frac{2 \left( \frac{1}{12} + \frac{\sigma_{img}^2}{N_{avg}} \right)}{SS^2 (MIG)^2}$$

Using image averaging to control noise is useful because it allows for varying image noise without changing any physical test parameters such as the camera or optics. Note that any non-random behavior in image intensity, such as changes in lighting or thermal effects in the camera, will cause deviation between the observed variance and the expected variance from Eq. (3).

II.3. Noise characterization using effective number of bits ($B_{eff}$)

One metric used in signal processing to measure the quality of an analog-to-digital conversion process is the effective number of bits ($B_{eff}$) [49]. This metric has been solved for signal-processing and signal-generating systems (see ENOB in [49]), but must be re-derived for imaging systems because the underlying assumptions are not the same (the input signal does not vary sinusoidally in a camera). Deriving $B_{eff}$ begins with a definition of the signal-to-quantization-noise ratio (SQNR):

$$SQNR = \frac{\mu^2}{\sigma_0^2}$$

Where $\mu =$ the mean intensity value of a single pixel. This quantity can be re-written in terms of the number of bits, B:

$$\mu = (2^B - 1)\mu_0$$

Where $\mu_0$ is a bit depth independent measure of the mean ($\mu_0 \in [0,1]$).

Substituting the known value of 1/12 for $\sigma_0$ yields:

$$SQNR = \left( \frac{(2^B - 1)\mu_0}{\frac{1}{12}} \right)^2$$

$$= (\sqrt{12} \cdot (2^B - 1)\mu_0)^2$$

This can be rearranged to solve for B:
\[ B = \log_2 \left( \frac{\sqrt{SQNR}}{\sqrt{12} \cdot \mu_0} + 1 \right) \]  

Equation (17) represents the number of bits used for quantization given a bit-depth-normalized mean (\( \mu_0 \)) and the SQNR. The effective number of bits, then, is what results from Eq. (17) if the signal-to-noise ratio (\( SNR = \mu^2 / \sigma^2 \), where \( \sigma^2 \) includes all sources of noise, not just quantization) is used instead of the SQNR. Substituting and simplifying yields Eq. (18):

\[ B_{eff} = \log_2 \left( \frac{\sqrt{SNR}}{\sqrt{12} \cdot \mu_0} + 1 \right) \]

\[ = \log_2 \left( \frac{\mu^2}{\sqrt{\sigma^2} \cdot \sqrt{12} \cdot \mu_0} + 1 \right) \]

\[ = \log_2 \left( \frac{1}{\sigma \sqrt{12}} \left( \frac{\mu}{\mu_0} \right) + 1 \right) \]

\[ = \log_2 \left( \frac{1}{\sigma \sqrt{12}} \left( 2^B - 1 \right) + 1 \right) \]

\[ = \log_2 \left( \frac{1}{\sigma \sqrt{12}} \left( 2^B - 1 + \sigma \sqrt{12} \right) \right) \]

\[ = \log_2 \left( 2^B + \sigma \sqrt{12} - 1 \right) - \log_2 (\sigma \sqrt{12}) \]  

Equation (18)

If \( \sigma \) is very small compared to \( 2^B \), then \( \sigma \sqrt{12} - 1 \) becomes negligible in comparison and \( B_{eff} \) simplifies further to Eq. (19):

\[ B_{eff} \approx \log_2 2^B - \log_2 (\sqrt{12} \cdot \sigma) \]

\[ \approx B - \log_2 (\sigma) - 1.79 \]  

Equation (19)

Where \( B \) is the actual number of bits and \( \sigma \) is the standard error of pixel intensity (or, for other types of measurements, the standard error of the measurement in question assuming zero noise bias). It should be noted that if the only significant noise source present is quantization noise, then \( \sigma = \sigma_Q = 1/\sqrt{12} \) and Eq. (19) becomes \( B_{eff} = B \). This results in a simple metric which can be used to evaluate the quality of an image in terms of bits, which can then be used to optimize the number of bits used for recording images.
III. METHODS

To determine the effectiveness of increasing the bit depth of the camera, a sample must first be prepared and mounted, instruments must be calibrated, and the baseline noise of the camera must be assessed. These steps are recorded in Sections III.1-III.3 below. Section III.4 details the method used to determine the effect of bit depth on DIC at room-temperature. In section III.4, this method is extended to evaluate the effect of increased bit depth at elevated temperatures.

III.1. Sample preparation and equipment setup

The sample and equipment used for this work are similar to that used by Thai et al in [21], as follows. A graphite rod purchased from GraphiteStore.com [56], which was previously milled in the center to have a square cross section of nominal width 7.62 mm (0.3 in), was lightly sanded and then speckled with Aremco Pyro-Paint 634-AL using a toothbrush speckling method [21]. The toothbrush method consists of dipping a toothbrush in paint and flicking the bristles toward the specimen such that paint lands on the specimen in a random pattern. The paint was dried for 2 hours at room-temperature and then cured for 2 hours at 200 °F per the manufacturer’s instructions. The graphite sample and dimensions, as measured by digital calipers, are shown in Figure 2.

![Figure 2: Graphite sample dimensions](image)

After the paint was fully cured, the sample was mounted in the vacuum test chamber of a Gleeble 1500D thermo-mechanical load frame. For this work, the loading mechanism for the load frame was disabled and only the thermal component was used. Custom-made copper grips were used to mount the sample to the load frame. Heating the sample in the Gleeble was done by passing electrical current through the sample with temperature feedback using a type-k thermocouple, in this case Omega Alumel/Chromel
wire welded at the junction. To ensure sufficient electrical conductivity between the grips and the sample, graphite powder was applied to the inside of the grips between the grip and the sample. The thermocouple was held against the sample using tension. Figure 3 shows the mounted sample.

![Figure 3: Sample mounted in the Gleeble](image)

After the sample was mounted, the vacuum chamber of the Gleeble was sealed and an aluminum frame with the camera equipment was mounted on top of the chamber. Camera equipment used included a FLIR A6751sc thermal camera, a micrometer-driven translation stage holding a single Basler Ace acA4600-10uc color camera, and a pair of CCS LDR2-90BL2 blue LED ring lights. The Basler was equipped with an 8mm lens set at aperture f/8. A Process Sensors Corporation Metis MQ11 2-color pyrometer, Serial #7204, was mounted to a separate fixture on the Gleeble. This fixture allowed the pyrometer to be moved out of the way when not in use without disturbing the optical equipment. The frame, camera, lights, and pyrometer are shown in Figure 4.
After mounting the camera, the vacuum chamber was evacuated to a pressure on the order of $10^{-2}$ torr to reduce oxidation of the sample at high temperatures. This setup was used for all of the following tests with only minor modifications.

**III.2. Calibrating the temperature measurement and control system**

The temperature controller was only calibrated for use with type K thermocouples, which have a maximum temperature rating of 1200 °C, and for the pyrometer, which is rated between 800-2000 °C. However, because the temperature of the center of the specimen was expected to range from room-temperature to 1600 °C, neither instrument could provide temperature control by monitoring the center of the specimen. Thus, an alternative method was required for temperature measurement and control.

To overcome the problem of temperature control, a type-k thermocouple was installed at one end of the specimen near the water-cooled grips, which do not reach as high of temperatures. The temperature at the center of the sample could then found by calibrating the temperature at the center of the specimen as a function of the temperature at the side. Preliminary data of the relationship is shown in Figure 5, where the blue points are data of the sample temperature at both the center (TC1) and side (TC2) of the specimen.

![Figure 4: (a) camera and lighting setup, and (b) location of camera and lights relative to the sample](image-url)
and the red line is a fit of the data. This method was used in [21] to obtain the sample temperature for the same graphite sample as is used in this work, and the temperatures were found to be linearly proportional. For this work, 0.01” diameter type-k thermocouple wire, which was the diameter used during the Gleeble’s temperature calibration, was used for both thermocouples.

![Graph showing temperature calibration](image)

**Figure 5: Example calibration of the side thermocouple (TC2) to the center thermocouple (TC1).**

The linear relationship between the two temperatures is most valid for lower temperatures in a vacuum chamber where heat transfer is primarily through conduction, but the relationship is likely to become nonlinear as temperature increases and radiation heat transfer becomes significant. Thus, it was necessary to use the pyrometer to measure the sample at higher temperatures because TC2 cannot be calibrated for sample temperatures higher than 1200 °C. Figure 6 shows the sample setup used for calibrating the temperature measurements.
Because measurements from a 2-color pyrometer are highly dependent upon the emissivity ratio of the sample at the two wavelengths measured by the pyrometer, the pyrometer was calibrated at the same time as TC2. This was done by heating the sample to 1200 °C and adjusting the emissivity ratio of the pyrometer in the manufacturer-provided software. The value which yielded the closest match for this rough comparison was $\epsilon_1 / \epsilon_2 = 1.1$. This was supplemented by a separate temperature fit done in post-processing as described below.

It can be shown that the true temperature of an object can be determined using the temperature measured by a 2-color pyrometer, the emissivity ratio used by the pyrometer, and the true emissivity ratio of the object. This relationship is shown in Eq. (20), which is derived from Eq. (8) in [57].

$$T = \frac{1}{T_R} + \frac{\ln \left( \frac{\epsilon_1}{\epsilon_2} \right) - \ln \left( \frac{\epsilon_1'}{\epsilon_2'} \right)}{C_2 \left( \frac{1}{\lambda_2} - \frac{1}{\lambda_1} \right)}^{-1}$$  \hspace{1cm} (20)

Where:

$T = $ true temperature of the sample [K]

$T_R =$ temperature measured by the pyrometer [K]

$\lambda_1, \lambda_2 =$ two wavelengths of radiation measured by the pyrometer

$I_{\lambda_1}, I_{\lambda_2} =$ spectral intensity measured by the pyrometer at each wavelength

$\epsilon_1, \epsilon_2 =$ emissivities of the sample at $\lambda_1$ and $\lambda_2$, respectively, as used in the original pyrometer measurement

$\epsilon_1', \epsilon_2' =$ true emissivities of the sample at $\lambda_1$ and $\lambda_2$ respectively
\( K_1, K_2 \) = a pyrometer-specific constant encompassing geometric factors, optics, etc.

\( C_2 = \frac{hc}{k_B} \) Planck’s second radiation constant

It should be noted that all of the variables in Eq. (20) except \( T, T_R \), and \( \varepsilon_1'/\varepsilon_2' \) are either physical constants or properties of the pyrometer. As such, any variation in these parameters is assumed to be accounted for in the stated accuracy of the instrument, allowing them to be treated as constants for analytical purposes. As for the \( \varepsilon_1'/\varepsilon_2' \) term, it is assumed to be constant with respect to temperature. This allows the second term in Eq. (20) to be lumped into a single constant \( C \), as shown in Eq. (21). Although temperature independence of \( \varepsilon_1'/\varepsilon_2' \) is not necessarily true, it can be verified for temperatures less than 1200 °C and is assumed to be negligible for temperatures between 1200-1600 °C. In the event of disagreement between results contained herein and results from outside sources, the assumption of temperature independence is likely the largest source of error for temperature measurement beyond 1200 °C.

\[
T = \left( T_R^{-1} - C \right)^{-1} \tag{21}
\]

Where:

\( T = \) true temperature of the sample [K]

\( T_R = \) temperature measured by the pyrometer [K]

\( C = \) an empirical constant dependent upon the material emissivity and other factors.

The constant \( C \) can be easily solved for using \( T \) and \( T_R \) data obtained during calibration.

Having established methods for temperature measurement, control, and calibration, a temperature calibration sequence was performed on the Gleeble. The calibration setup is shown in Figure 7(a) where TC1 is the thermocouple at the center of the specimen, TC2 is placed 35 mm offset from the center, and the pyrometer is positioned to measure temperature at the location indicated. Figure 7(b) shows the temperature vs time curve used to control the sample’s temperature; the curve is composed of a series of 5-second heating periods followed by 10-second dwell periods at temperatures up to 1100 °C in increments of 25 °C.
Figure 7: (a) Thermocouple/Pyrometer Calibration setup, and (b) Applied temperature history of TC1

This sequence was run while collecting data from both thermocouples and the pyrometer. The data was then used to generate a calibration fit using the methods described previously. The time-series data from this calibration is shown in Figure 8. The temperature from TC1 was step-wise linear, which is consistent with the applied temperature vs time curve in Figure 7(b). The curve for TC2 appears to be nearly step-wise linear, except the ‘steps’ show the temperature decreasing with time after reaching each peak. This would be of concern since it could skew the calibration, but the skewing effect is counteracted here by using a temperature series which increased and then decreased the temperature at the same rate. The pyrometer read a constant temperature at 796 °C until the sample temperature exceeded 796 °C, at which point the pyrometer measurement matched the TC1 temperature closely while temperature was increasing. As temperature decreased, however, the two measurements deviated slowly over time.
Figure 8: Time-series data from temperature calibration

To show the relationship between each measurement method, TC2 and the Pyrometer are shown as a function of TC1 in Figure 9. The plot also shows the fits generated from these data which map the two temperature measurements to the temperature at the sample center. In this temperature range, the fits both agree with each other relatively well.
Figure 9: Temperature calibration fits

After completing setup and calibration, the equipment was ready for imaging. For the following sections, the experimental setup was left identical to the setup in the previous sections with the exception that the center thermocouple (TC1) was removed.

III.3. Noise study

To determine the effect of bit depth on DIC uncertainty, it was necessary to ensure that a change in bit depth was not overshadowed by a high level of noise in the image. To this end, a series 256 of images was taken at room-temperature for each combination of exposure time and bit depth in Figure 10. Of these 256 images, $N_{avgd}$ were randomly selected, averaged, and the averaged image was saved for each value of $N_{avgd}$ shown. This process was repeated 30 times resulting in a total of 199,680 images taken and 7800 averaged images saved.
<table>
<thead>
<tr>
<th>Exposure Times [µs]</th>
<th>2 Bit depths (B)</th>
<th>10 numbers of images averaged (N_{avgd}) [images/DIC image]</th>
<th>Repeated 30x</th>
<th>7800 averaged images saved</th>
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<tbody>
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**Figure 10: Test matrix for noise and room-temperature DIC studies**

To quantify the properties of the camera used, several DIC-relevant metrics were calculated across each series of 256 single images and across each series of 30 averaged images. Because the camera is a color camera and the blue channel is of the most interest for high-temperature measurements, all metrics (and DIC in later sections) were calculated for only the blue channel. The following metrics were calculated:

- The minimum and maximum pixel intensity
- Image noise, calculated using Eq. (22)

\[
\sigma_{img}^2 = \overline{\sigma_i^2} = \frac{1}{HW} \sum_{i=1}^{H} \sum_{j=1}^{W} (\sigma_i(i,j))^2
\]  

(22)

Where:

\[
\sigma_i(i,j) = \sqrt{\frac{1}{N-1} \sum_{k=1}^{N} (I_k(i,j) - \mu_i(i,j))^2}
\]

\[
\mu_i(i,j) = \frac{1}{N} \sum_{k=1}^{N} I_k(i,j)
\]

- \(\sigma_{img,exp}\) (See Eq. (12))
• MIG for the $N_{avg_d} = 256$ image as defined in Eq. (5). Derivatives were calculated using a central difference approximation. The averaged image was used at the suggestion of Phil Reu [30] in order to eliminate false gradients due to image noise.

• $\Delta$ (See Eq. (2))

• $B_{eff}$ (see Eq. (19)), calculated using $\sigma_{img}$

• $\sigma_{DIC,exp}$ (See Eq. (13))

Once the images were collected, the noise and other calculations were performed and used to inform the remainder of the research. As a part of this study, the effectiveness of image averaging was assessed to determine whether it is a viable method of controlling image noise. Because image averaging is used in this work to control apparent noise in an image, the terms “high-noise” and “low-noise” will be used when comparing non-averaged and averaged images, respectively.

**III.4. Room-temperature DIC study**

To determine the uncertainty of the DIC measurement, the images taken during the noise study (see Figure 10) were processed in VIC-2D using a 566x136 pixel region of interest (ROI), the ZNSSD criterion, a subset size of 27 pixels, and a subset spacing of 5 pixels. The mean and standard error of the DIC displacement measurement were then calculated for each image, similar to the method used in [58]. Important to note here is that these metrics are a measure of spatial statistics, meaning they are measured across some region in space, as opposed to temporal statistics which are measured at the same location across time (see [59] for a more in-depth discussion of spatial vs temporal measurements). Although the two are not the same, they are assumed equivalent for comparison between the settings under investigation here since no strain is applied to the sample. Using the DIC data, the relationship between DIC uncertainty, bit depth, exposure time, and $N_{avg_d}$ (which controls image noise) were analyzed and compared to predicted values.

**III.5. High-temperature DIC study**

After taking and analyzing images at room-temperature, images were taken at varying exposure times, bit depths, temperatures, and values of $N_{avg_d}$ according to Figure 11. For the bit depths, a ‘d’ denotes the image was a scaled-down version of the next-higher bit depth format which the camera could
output (8- or 12-bit); for example, ‘8d’ means the image was produced by taking the 12-bit image and dividing by a value of $2^4 = 16$ and saved as an integer-valued image. Image metrics and DIC were performed using the same methods and settings as in the room-temperature study. This resulted in a total of 91520 images taken, 2860 averaged images saved, and 1430 DIC correlations performed.

<table>
<thead>
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<th>13 Exposure Times [μs]</th>
<th>×</th>
<th>5 Bit depths</th>
<th>×</th>
<th>$2 N_{avgd}$ [images / DIC image]</th>
<th>×</th>
<th>11 Target temperatures (TC1) [°C]</th>
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**Figure 11: Test matrix for high-temperature study**

Temperature was measured using the procedure outlined previously (See section III.2). Figure 12 shows the estimated temperature at the center of the sample vs the target temperature, where the estimates are calibrated measurements from TC2 and the pyrometer. The two temperature estimates agree within 40 °C at a 900 °C target temperature, but then diverge as temperature increases. As such, it was necessary to select what measurements were considered most accurate at each temperature. Because the pyrometer measurement was taken at the center of the sample and did not rely on a consistent temperature distribution across the sample, it was considered most accurate for those temperatures it could measure. For $T \leq 900$, the calibrated temperature estimate based on TC2 was used because this was near or below the low-limit of the pyrometer’s temperature range. For $T > 900$ °C, the pyrometer measurement was assumed most accurate because it was taken directly at the center of the sample, and thus did not depend on a consistent temperature distribution at the various temperatures. In both cases, the method deemed most accurate was
used as the control variable for the Gleeble during acquisition. This results in the measurement at these points appearing like a line of perfect agreement between estimate and target temperature in the plot.

![Graph showing estimated vs target temperature using calibrated estimations from TC2 and the pyrometer. Temperature estimates for the two methods diverge as temperature increases.](image)

**Figure 12:** Estimated vs target temperature using the calibrated estimations from TC2 and the pyrometer. Temperature estimates for the two methods diverge as temperature increases.

After image acquisition and DIC were completed, the mean and standard error of displacement were calculated across each image and the results were analyzed.
IV. RESULTS

The following sections include results from the noise, room-temperature DIC, and high-temperature DIC studies.

IV.1. Noise study

As described in section III.3, a series of images were saved for a range of exposure times, values of $N_{\text{avg}}$, and bit depths. The results in this section discuss the effect of each variable on image intensity and noise, beginning with a baseline and then moving to exposure time and $N_{\text{avg}}$.

The baseline settings for this work are room-temperature, 8-bit, non-averaged ($N_{\text{avg}} = 1$) images taken with an exposure time of 4410 µs. These settings were chosen to most closely mimic standard test conditions and to minimize $\Delta$ while maintaining a minimum of 50 counts as suggested by Thai et al for high-temperature DIC [21]. An image taken with these settings is shown alongside the equivalent 12-bit image in Figure 13. Also included in the figure are the region of interest (ROI) used for calculations and the accompanying histogram, $Z_1$ (5th percentile marker), $Z_2$ (95th percentile marker), $\Delta$ (Eq. (2)), MIG (Eq. (5)), $\sigma_{\text{img}}$ (Eq. (22)), and $B_{\text{eff}}$ (Eq. (19)). Note MIG was calculated for the $N_{\text{avg}} = 256$ image (or, in the high-temperature study, for the $N_{\text{avg}} = 64$ image) per Phil Reu’s recommendation discussed previously [30] and $\sigma_{\text{img}}$ and $B_{\text{eff}}$ were of necessity calculated across the series of 256 images, not from a single image like the other metrics were. In the figure, the histograms are of a roughly bell-shaped curve with $\Delta>50$, which suggests a good-quality speckle pattern with sufficient contrast for DIC measurements.

Comparing the 8- and 12-bit images in Figure 13 yields a few important observations. Visually, the two images look the same. The histograms have a similar shape except that the 12-bit histogram is thicker, or has more variation of bin height from value to value. The primary difference between the two is the x- and y-axes of the 12-bit histogram are roughly 16x smaller and larger, respectively, than that of the 8-bit image. This is expected since at 12-bit the camera uses a maximum integer value of $2^{12} - 1 = 4095$ to store intensities and at 8-bit the camera only has a maximum integer value of $2^8 - 1 = 255$. Thus, the scales of both are expected to differ by a factor of $(2^{12} - 1)/(2^8 - 1) \approx 16$. 
Figure 13: Example 8-bit and 12-bit images, where all other settings are baseline (Baseline settings for this work are 8-bit, room-temperature, non-averaged images with a 4410 µs exposure time).

Increasing bit depth scales the value of individual pixels to create the same image.

The relationship between exposure time, image intensity, and image noise are shown for 8-bit images in Figure 14. At the top of the figure are three sample images with the associated histograms plotted in the same format as Figure 13. Beneath the example images are plots of $Z_1$, $Z_2$, $\Delta$, MIG, $\sigma_{\text{img}}$, and $B_{\text{eff}}$ vs exposure time. All settings except exposure time are baseline. Based on the data shown, image intensity ($Z_1$ and $Z_2$) and contrast ($\Delta$ and MIG) have a linearly proportional relationship with exposure time. As for image noise, $\sigma_{\text{img}}$ tends to increase with exposure time, which causes $B_{\text{eff}}$ to decrease.
Figure 14: The relationship between image intensity, $Z_2$, $\Delta$, MIG, $Z_1$, $B_{\text{eff}}$, and $\sigma_{\text{img}}$ vs exposure time.

At the top are three example images with the associated histograms, and on the bottom are plots of each metric vs exposure time. Maximum intensity, $\Delta$, MIG, and minimum intensity each vary proportionally with exposure time. $\sigma_{\text{img}}$ increases and $B_{\text{eff}}$ decreases as exposure time increases.

Figure 15 shows the same data as Figure 14, but for 12-bit images. As before, the histograms are ‘thicker’ and pixel intensities are scaled in magnitude compared to the 8-bit images. The magnitude of $B_{\text{eff}}$, however, does not significantly increase for 12-bit images relative to the 8-bit images. This suggests the increase in bit depth for non-averaged images resulted in a negligible difference in terms of dynamic
range (where dynamic range is calculated as the ratio between the maximum value and the square root of noise).

Figure 15: The relationship between image intensity, $Z_2$, $\Delta$, MIG, $Z_1$, $B_{eff}$, and $\sigma_{img}$ vs exposure time for 12-bit images at otherwise baseline settings. At the top are three example images with the associated histograms, and on the bottom are plots of each metric vs exposure time. Values and plots for 12-bit images hold the same trends as for 8-bit images (See Figure 14), but values are scaled in magnitude; the exception to this trend is $B_{eff}$, which is unchanged.
The effect of image averaging is shown in Figure 16, where $\sigma_{img}$ and $B_{eff}$ are plotted as a function of the number of images averaged for 8- and 12-bit images. Predicted values according to Eq. (12) are also shown. Observed noise in the 8-bit images matches predicted values closely. For the 12-bit images, observed values deviate increasingly from expected values as the number of images increases and $\sigma_{img}$ decreases. This deviation is likely due to non-random behavior in the images, such as periodic variation in light source intensity or vibration of the Gleeble. 12-bit averaged images show lower levels of noise and higher $B_{eff}$ than their 8-bit counterparts when $N_{avgd}$ is high. When $N_{avgd} > 32$, $B_{eff} > 8$ for 12-bit images taken with this camera and these settings (4410 µs, sample at room-temperature).

![Figure 16: Observed and predicted image noise (top) and $B_{eff}$ (bottom) as a function of the number of images averaged ($N_{avgd}$). Image noise tends to decrease as predicted by Eq. (12) with some deviation, especially at lower noise / higher $B_{eff}$. Noise for 12-bit averaged images is lower than for 8-bit averaged images.](image)

IV.2. Room-temperature DIC study

Example correlations of 8- and 12-bit images at otherwise baseline settings are shown in Figure 17 (baseline settings for this work are room-temperature, 8-bit, non-averaged images with an exposure time of 4410 µs). Note that 30 repeat images were saved at these settings as recorded in Figure 10 (where each of
the 30 ‘repeats’ involved taking 256 consecutive images and randomly selecting both a single image to save and multiple images to average and save), but one image was used as the reference and the other 29 were correlated against the first. In Figure 17, the plots of horizontal displacement (u) exhibit a noisy, non-regular pattern having a similar range for both 8- and 12-bit non-averaged images.

Figure 17: Measured horizontal displacement of example 8-bit and 12-bit images. Magnitudes of displacement (nominally zero) are of a similar range for both bit depths. Displacement contours show approximately random behavior.

Figure 18 shows the spatial mean and 1-σ standard error (standard deviation) of all 29 correlations for the two series. Data points are offset slightly in the horizontal direction for readability. Mean values show a non-zero bias, which suggests the camera moved relative to the specimen over the course of acquisition. This drift is relatively low compared to the size of the uncertainty bands. In spite of the drift, the size of the uncertainty bands is consistent across the series. Like Figure 17, comparison of the uncertainty bands here does not reveal a significant difference between 8-bit and 12-bit images at baseline settings.
Figure 18: Spatial mean and standard error of horizontal displacement (u) for 8- and 12-bit correlated images taken at otherwise baseline settings. The means shows a non-zero bias, which suggests movement of the camera during acquisition, but the standard errors are consistent across all images. Comparison of 8- and 12-bit images shows no significant difference.

Figure 19 shows the observed spatial standard error of horizontal displacement as a function of exposure time along with predicted temporal standard error from Vic-2D (where each data point shown is the square root of the mean of the squares of predicted uncertainty across all subsets in the image) and Eq. (9). All settings except exposure time and bit depth are baseline. The measured standard errors at the 210 µs exposure time, which were excluded from the plot window to make the plot easier to read, were 1.3 pixels and 0.53 pixels for 8- and 12-bit respectively. Spatial standard error tends to be larger than predicted temporal standard error but follows the same trends with respect to exposure time (and thus with respect to Δ and MIG – see Figure 14). As exposure time increases, both observed and predicted random error decrease asymptotically.
Figure 19: Observed and predicted displacement standard error as a function of exposure time where all other settings are baseline. Predicted values are calculated using either Eq. (9) or reported values from Vic-2D. Both predicted and observed DIC displacement standard error decrease asymptotically as exposure time increases.

The spatial mean and $1 \cdot \sigma$ standard error of horizontal displacement is shown as a function of $N_{avgd}$ in Figure 20. All other settings are baseline. For the series, mean values generally center around a constant value, and variation of the mean decreases as $N_{avgd}$ increases. Random error also diminishes as $N_{avgd}$ increases.

Figure 20: Mean and standard error of horizontal displacement as a function of $N_{avgd}$ where all other settings are baseline. Standard error decreases as $N_{avgd}$ increases.

To more effectively compare random error between 8- and 12-bit images, Figure 21(a) shows the displacement standard error (the size of the uncertainty bands in Figure 20) from 8- and 12-bit images at
multiple values of $N_{avgd}$. From this absolute perspective, the two bit depths are nearly indistinguishable. However, it is not the absolute reduction of error which is of interest – it is the relative improvement which happens when moving from 8-bit to 12-bit images. To highlight this improvement, Figure 21(b) shows $\sigma_{u_{12}}/\sigma_{u_8}$, or the 12-bit standard error divided by the 8-bit standard error. The plot also includes a line of ‘no improvement’ at $\sigma_{u_{12}}/\sigma_{u_8} = 1$, which represents no difference between the 8- and 12-bit measurements. When $\sigma_{u_{12}}/\sigma_{u_8}$ is lower than this line, moving from 8-bit to 12-bit images improves the measurement. As $N_{avgd}$ increases, which decreases image noise, moving from 8-bit to 12-bit images increasingly reduces DIC displacement standard error.

![Diagram](image)

**Figure 21**: Comparison of 8- and 12-bit DIC displacement standard error as a function of $N_{avgd}$ at otherwise baseline settings. Part (a) is a plot of DIC displacement standard error vs $N_{avgd}$ for 8- and 12-bit images. Part (b) shows the 12-bit standard error divided by the 8-bit standard error ($\sigma_{u_{12}}/\sigma_{u_8}$), which illustrates the reduction in standard error achieved by moving from 8-bit to 12-bit images for varying values of $N_{avgd}$. As $N_{avgd}$ increases (noise decreases), the relative difference between 8- and 12-bit DIC random error increases.
The reduction of DIC displacement standard error due to increasing bit depth becomes more pronounced at low exposure times. Figure 22 shows the same data as Figure 21(b) for multiple exposure times. For the 4410 µs exposure time images, moving from 8-bit to 12-bit images produced a 34% reduction in random error for $N_{\text{avg}} = 256$. At a 735 µs exposure time, this reduction increased to 64%.

**Figure 22:** 12-bit standard error divided by the 8-bit standard error ($\sigma_{12}/\sigma_{8}$) at multiple exposure times. Increasing bit depth has a larger effect on DIC displacement standard error at lower exposure times.

### IV.3. High-temperature DIC study

As was observed in [21], heating the specimen tends to increase the overall brightness of the image. Figure 23 shows a series of sample images with the associated histograms (top) and a few image metrics as a function of temperature (bottom) for the images taken under otherwise baseline settings (Baseline settings for this work are 8-bit, room-temperature, non-averaged images with a 4410 µs exposure time). As temperature increased past ~900 °C, the images increased in both brightness ($Z_2$) and contrast ($\Delta$ and MIG) until the images began to saturate at ~1400 °C. After this point, the images continued to brighten, but contrast decreased until both $\Delta$ and MIG were equal to zero.
Figure 23: The relationship between image intensity, $Z_2$, $\Delta$, MIG, $Z_1$, $B_{eff}$, and $\sigma_{img}$ vs temperature. At the top are three example images with the associated histograms, and on the bottom are plots of each metric vs exposure time. Prior to saturation, increases in temperature tend to increase both brightness and contrast, but after saturation begins, increases in temperature reduce contrast.

Speckle pattern inversion [60–62], or the switching from dark pixels to light pixels and vice versa as temperature increases, was also observed. The inversion can be seen by comparing the 25 °C image to the 1300 °C image in Figure 23. Speckle pattern inversion can make DIC difficult or impossible because
subsets in the high-temperature image are now the opposite of what they were in the room-temperature image. Because images in this work were correlated using reference images at the same temperature, the inversion was not prohibitive for DIC, but reduced contrast at the point of inversion caused unique correlation behavior as discussed later on. Correlation against images at the same temperature is not typical for practical measurements, and the DIC user taking measurements under this temperature range will need to find a way to overcome the inversion such as that used for static tests in [62].

Although Figure 23 shows brightness and contrast trends which are somewhat characteristic of the high-temperature images taken, they do not provide data across all images. Figures 24 and 25 expand upon this, first showing $Z_2$ and MIG for 8-bit averaged images in Figure 24 and then showing $\Delta$ and MIG for multiple bit depths in Figure 25.

In Figure 24, $Z_2$ and MIG are shown as a function of exposure time and temperature. White gridlines denote an actual temperature or exposure time used, and the intersection of each gridline is the location of a measured data point. All other regions in the colormap are linearly interpolated values. As observed previously, increasing exposure time at room-temperature increases both $Z_2$ and MIG. However, as the temperature increases past the point of saturation (the yellow region in $Z_2$), the MIG reaches a peak and then diminishes. At lower exposure times, image saturation and peak MIG occur at higher temperatures. In the region of 1200-1300 °C, the value of MIG at its peak is lower than at other temperatures; this is likely because the image is only partway through the process of speckle pattern inversion, which would reduce contrast.
Figure 24: The MIG and $Z_2$ of all 8-bit images vs exposure time and temperature. MIG tends to increase with exposure time and temperature until saturation occurs, after which MIG quickly decreases.

As an expansion of Figure 24, Figure 25 shows $\Delta$ and MIG values for all exposure times and bit depths. In the figure, several plots of MIG and $\Delta$ are presented in the same format as Figure 24 and organized by bit depth (as listed in Figure 11). The plots of MIG and $\Delta$ appear to follow roughly the same trends, which is not surprising since the two metrics were shown to scale proportionally with exposure time in Figure 14, though there is some difference between the two around the point of speckle inversion (1200-1300 °C). As bit depth increases, the scale increases with the maximum value, but distribution of values does not change significantly for either MIG or $\Delta$. 
Figure 25: Δ and MIG for all exposure times, bit depths, and temperatures in the high-temperature study. MIG and Δ both follow nearly the same trends vs exposure time, temperature, and bit depth.
Figure 26 shows the standard error of horizontal displacement as a function of exposure time and temperature for all captured bit depths. The figure includes several plots in the same format as Figure 24 organized by bit depth and high-noise ($N_{avg} = 1$) vs low-noise ($N_{avg} = 64$). Note the 8-bit and 8d-bit plots (‘d’ meaning the images were derived from the next higher bit depth image taken by the camera) are nearly identical; this suggests the 4d-8d- and 10d-bit derived images were equivalent to natively 4- 8- or 10-bit images for the purpose of this study.

A few observations are important here which are true for all of the plots in Figure 26. As observed previously, DIC standard error increases as exposure time decreases at room-temperature. As temperature increases past 1100 °C, however, the region where random error is lowest shifts toward lower exposure times. This low point in $\sigma_u$ occurs close to the MIG and $\Delta$ peaks observed in in Figures 24 and 25. Increasing temperature or exposure time beyond this point leads to image saturation and failure of the correlation, as shown by the blank regions in the upper right corner of the plots.

Comparing between bit depths in Figure 26 is informative. Moving from 4-bit to 8-bit images produces a dramatic decrease in random error for both high-noise and low-noise images. For high-noise images, the remaining plots (8-bit, 8d-bit, 10d-bit, and 12-bit) are nearly identical – no improvement resulted from increasing bit depth. For low-noise images, however, moving from 8-bit to 10d- or 12-bit did reduce DIC random error at the same exposure times and temperatures. This is seen at lower temperatures as a shift of the blue and violet region to the left as bit depth increases. The difference in behavior between high-noise and low-noise images is as expected, since increasing bit depth is only expected to reduce DIC error if image noise is sufficiently low (See Eq. (10)).
Figure 26: DIC spatial standard error for high-noise ($N_{\text{avg}}=1$) and low-noise ($N_{\text{avg}}=64$) images between 25-1600 °C. If image noise is low enough, increasing bit depth reduces DIC standard error.
V. DISCUSSION

The first two subsections below discuss the effect of changing bit depth on DIC displacement uncertainty in the room-temperature and high-temperature studies. The remaining sections discuss the $\Delta$ metric at bit depths other than 8-bit and the spatial distribution of image noise.

V.1. Room-temperature DIC study - does increasing bit depth improve DIC?

High image noise in non-averaged images is a predictor for whether increasing bit depth will improve DIC. In the discussion of Eq. (10), it was predicted that if image noise from sources other than quantization ($\sum \sigma_i^2$) is higher than approximately 1/12, then increasing bit depth is not expected to produce a significant difference in DIC displacement uncertainty. Inspection of Figures 17-22 shows that, for the camera used, when images are not averaged, no significant difference exists between DIC displacement results using 8-bit vs 12-bit images. Taking the baseline images as an example, $\sigma_{img}$ for these images was 2.11 counts. Taking out quantization noise (using the equation $\sqrt{\sigma_{img}^2 - 1/12}$) results in a standard error of 2.09 counts – only 0.02 counts difference. Thus, it is not surprising that no significant difference was achieved by increasing bit depth under baseline settings, since quantization noise was a small portion of the total noise in the 8-bit images.

In contrast to the baseline image, correlations of low-noise, averaged images were shown to benefit from higher bit depth. As seen in Figure 22, the effect on DIC random error due to increasing from 8- to 12-bit images moves from no significant change to consistent and significant improvement as $N_{avgd}$ increases. However, this improvement begins at different numbers of $N_{avgd}$ for different exposure times. Plotting these same data as a function of $B_{eff}$, however, shows a more consistent trend, as seen in Figure 27. Here, similar to Figure 22, the 12-bit standard error divided by the 8-bit standard error ($\sigma_{u12}/\sigma_{u8}$), which indicates the reduction in standard error achieved by moving from 8-bit images to 12-bit images, is plotted as a function of $B_{eff}$, a measure of the dynamic range of the camera, for exposure times ranging from 735 $\mu$s to 12005 $\mu$s. At lower values of $B_{eff}$, the data tend to hover around the line of no improvement. As $B_{eff}$ increases, the data show a downward trend (if a data point is below the line of no improvement, moving from 8-bit to 12-bit images improves DIC). This downward trend begins as early as
\( B_{\text{eff}} = 6 \). Once \( B_{\text{eff}} \geq 8 \), all data points show at least some improvement from using 12-bit images instead of 8-bit images.

Figure 27: 12-bit DIC random error divided by the 8-bit DIC random error as a function of \( B_{\text{eff}} \). As \( B_{\text{eff}} \) increases, using 12-bit images instead of 8-bit images for DIC results in an increasing reduction in DIC random error.

Based on the data shown, one way to determine the appropriate number of bits for image capture and storage is to find \( B_{\text{eff}} \) for the experimental setup in question. This can be done by taking a series of at least 30 images at the maximum bit depth of the camera, calculating \( \sigma_{\text{img}} \) within the region of interest
using Eq. (22), and calculating $B_{\text{eff}}$ using Eq. (19). It is recommended by the author that the number of bits used to capture and store images be minimized, but be at least 1-2 bits greater than $B_{\text{eff}}$. Increasing bit depth beyond this number may increase required storage space, but is not likely to produce an improvement in DIC uncertainty. The ability to use $B_{\text{eff}}$ to determine the appropriate number of bits for DIC images is significant because $B_{\text{eff}}$ can be calculated prior to digital image correlation, allowing the user to determine whether 8-bit or higher-bit images should be used before the experiment begins.

V.2. High-temperature DIC study - using increased bit depth to improve high-temperature DIC measurements

Increased bit depth can be leveraged to reduce exposure time without compromising measurement precision. Consider, for example, the plots of displacement standard error vs exposure time for 8-, 10d-, and 12-bit averaged room-temperature images in Figure 28. The standard error of the 8-bit, 4410 µs correlations (the baseline images) was 0.0083 px. On the 12-bit curve, the 3360 µs images had a standard error of 0.0080. This range of exposure times is shown as an enlarged section in the figure. By using 12-bit 3360 µs images instead of 8-bit 4410 µs images, indicated by the green arrow in the enlarged section, the brightness of the images can be reduced with no loss in measurement precision.

Figure 28: $\sigma_u$ vs exposure time for 8d-bit, 10d-bit, and 12-bit images (room-temperature, $N_{\text{avg}} = 64$). For averaged images, 12-bit DIC data exhibit similar standard error values to 8-bit images, but at lower exposure times. An enlarged section of the range from 3360-4410 µs is also shown with a green arrow.
arrow representing the transition from 8-bit 4410 µs exposure time images (the baseline image set) to 12-bit 3360 µs exposure time images, which transition reduces both contrast and DIC random error.

By reducing the exposure time, the maximum temperature range of DIC can be increased. As a continuation of the example in the previous paragraph, Figure 29 shows $Z_2/(2^d - 1)$, a normalized metric of near-maximum pixel intensity, for 12-bit 3360 µs and 8-bit 4410 µs averaged images. As temperature increases, the maximum intensity of both image sets increases until saturation near 1400 °C. Note, however, that the 4410 µs images saturate at (or before) 1400 °C, whereas the 3360 µs images saturate sometime after 1400 °C but before 1500 °C. This means that increasing bit depth and reducing exposure time can allow for taking non-saturated images at higher temperatures without a reduction in DIC precision. Although the difference in temperatures is small here, roughly on the order of 10 °C based on the trajectory of the curves shown, a different experimental setup or method (i.e., a camera with lower noise or more images averaged) could increase this difference. If image noise is low enough, bit depth and exposure time can be leveraged to increase the maximum temperature range of DIC.

Figure 29: $Z_2$ vs Temperature under selected settings. All images are averaged (N_{avgd}=64). Images with a 3360 µs exposure time saturate at a higher temperature than images at a 4410 µs exposure time.

V.3. The Δ metric at varying bit depths

Comparison of the plots of $\sigma_u$ in Figure 26 for varying bit depths shows that for high-noise images, increasing bit depth beyond 8 bits does not significantly change DIC random error. However, increasing bit depth does increase $\Delta$ (see Figure 25). Thus, $\Delta$ alone is not a good indicator for whether an
image has sufficient contrast when using something other than the standard 8-bit images – a new recommendation is needed.

One method to convert $\Delta$ into a more general metric of image quality is to convert $\Delta$ into a percentage of the maximum value as shown in Eq. (23). Converting $\Delta$ to a percentage is consistent with the discussion of contrast in the iDICs Good Practices Guide [36], which recommends a minimum contrast of around 20% for an 8-bit camera [36]. However, the guide does not give specific guidance for different bit depths.

$$\Delta_{\%} = \frac{\Delta}{(2^B - 1)} \times 100\%$$  \hspace{1cm} (23)

Figure 30 shows $\sigma_u$ and $\Delta_{\%}$ vs bit depth for room-temperature, 6125 $\mu$s exposure time, high-noise (non-averaged) and low-noise ($N_{avgd} = 64$) images. For these data, a new DIC dataset was created using images at varying bit depths; images for the new dataset were derived from the 12-bit room-temperature images in the high-temperature study using the same conversion process that was used previously. $B_{eff}$ for the 12-bit image is also shown for reference in both plots, where $B_{eff}$ is calculated directly using $\sigma^2_{img}$ for the high noise images and using $\sigma^2_{img,exp}$ (See Eq. (12)) for the low-noise images.

In both plots in Figure 30, $\Delta_{\%}$ takes on similar values for both the high-noise and low-noise image sets. Observing how $\Delta_{\%}$ changes with bit depth shows that $\Delta_{\%}$ is generally constant, but varies more at low bit depths than at higher bit depths; this variation at low bit depths is attributed to quantization effects (rounding). Also in both plots, $\sigma_u$ tends to decrease with increasing bit depth until a certain point and then remains constant regardless of bit depth. This levelling-out point occurs roughly 1-2 bits higher than $B_{eff}$, which reinforces the earlier recommendation that the number of bits used for DIC images should be at least 1-2 bits greater than $B_{eff}$ in order to minimize both DIC random error and image storage space. Looking specifically at $B \geq 8$ for high-noise images, both $\Delta_{\%}$ and $\sigma_u$ stay nearly constant as bit depth increases. Thus, for a camera with typical noise properties, increasing bit depth will not significantly affect DIC random error. As such, it remains a good rule of thumb to ensure a minimum of 20% contrast between dark and light features for DIC images regardless of whether 8-bit or higher-bit images are used.
Figure 30: $\sigma_u$ and $\Delta_\%$ vs bit depth at otherwise baseline settings. For $B \geq 8$ bits, both $\sigma_u$ and $\Delta_\%$ remain consistent as bit depth increases.

Important to note here is that the 20% recommendation is only a starting point; if possible, the DIC uncertainty should be assessed directly prior to the experiment. This allows the user to determine whether the DIC measurement is precise enough for the experimental work and/or whether contrast can be safely reduced while maintaining sufficient measurement precision. As a rule of thumb for required measurement precision, Phil Reu gave a recommendation that $\sigma_u$ should be less than 0.005 pixels [30]. Random error can be calculated by taking images of the sample with zero nominal displacement or strain, performing DIC, and calculating the standard deviation of subset displacement.

V.4. Spatial distribution of image noise

Typical noise values were calculated for each run of 256 (room-temperature studies) or 64 (high-temperature study) images, but image noise is not uniform across an image. Figure 31 shows the standard error of all pixels in the room-temperature studies at baseline settings. In the figure, each point represents the mean and standard error of a single pixel within the ROI (See Figure 13). Color is used to indicate where multiple pixels overlap. $\sigma_{img}$ (the square root of the mean variance - see Eq. (22)) is shown as a black horizontal line. Pixel uncertainties tend to increase with the mean, and the distribution of pixel uncertainties appears to band together into three regions.
Figure 31: Pixel noise at baseline settings. Each point represents the sample standard error of a single pixel across 256 consecutive images. Color is used to indicate when multiple pixel uncertainties overlap. $\sigma_{\text{img}}$ is also plotted as a black horizontal line. Observed image noise varies from pixel to pixel and as a function mean pixel intensity.

Because the experiments were performed using a color camera, one might reasonably assume that the three bands correspond to the camera’s three color channels (red, green, and blue). However, the measurements were performed using only the blue channel. Upon closer inspection, the banding behavior is the effect of a spatial pattern in image noise which is shown in Figure 32. For this figure, a series of 1024 12-bit images of a white background were taken using the Basler camera. The figure shows the blue channel of the averaged image, the standard error image, and an enlarged section of the standard error image. The standard error image illustrates a repeating ‘plaid’ pattern of image noise across the camera sensor. When these uncertainties are paired with their respective mean values and plotted, it results in the banding behavior observed in Figure 31.
Figure 32: Mean and standard error of the blue channel of 1024 12-bit images of a white background taken using a color Basler camera. The standard error of pixel intensity varies in a repeating spatial pattern.

This plaid uncertainty pattern is explained by an article published by Cambridge in Colour [63]. In brief, a color camera with a Bayer filter array works by arranging pixels sensitive to either red, green, or blue light in a repeating 2x2 pattern as shown in Figure 33. Although each 2x2 group of pixels might be used to supply a single value for each color, most cameras don’t work this way. Rather, three color values are supplied in the image at each pixel location using interpolation. For example, if a given pixel on the sensor has a blue filter, then the blue intensity value will come directly from the pixel and the red and green values will be interpolated using either 2 or 4 nearby pixels, depending on the pixel location and the interpolation algorithm. The effect of interpolation on image noise is similar to the effect of image averaging - the more surrounding pixels used to interpolate with, the lower the apparent noise (once again, depending on the interpolation algorithm). Thus, the apparent uncertainty of a pixel’s color value will depend on whether the value is measured directly or interpolated, and how many pixels were used to interpolate. This variation results in the plaid uncertainty pattern in Figure 32 and the banding behavior in Figure 31.
The presence of interpolation in the raw image is troubling for DIC users. Interpolation is essential to the operation of DIC measurements, and the interpolation method used for DIC affects bias error [31]. As such, pre-interpolating the image to achieve higher resolution would almost certainly result in an increase of bias error in DIC measurements. It is the recommendation of the author to not use a color camera for DIC measurements if a monochrome camera is available. Alternatively, a DIC algorithm could be developed which adjusts for pre-interpolation in color images in order to reduce these errors.
VI. CONCLUSION

In this work, the effect of bit depth on high-temperature DIC measurements was investigated. The theoretical relationship between DIC displacement uncertainty and bit depth was determined. An equation to predict DIC displacement uncertainty in averaged images was derived. An expression for the effective number of bits ($B_{eff}$) was derived for imaging applications. Images were taken of a speckled sample at varying temperatures, exposure times, bit depths, and numbers of images averaged. DIC was performed on the images and the results discussed as a function of each variable. Some conclusions include:

- Image averaging reduces both image noise and DIC displacement random error.
- Increasing bit depth reduces DIC random error if image noise is sufficiently low; if image noise is high, the effect is negligible.
- $B_{eff}$ is an effective metric to determine the appropriate number of bits to capture and store images used for DIC. It is recommended by the author that the number of bits used to capture and store images be 1-2 bits greater than $B_{eff}$.
- Maintaining a minimum contrast of $\Delta_R \geq 20\%$ (See Eq. (23)) for DIC images is a good rule of thumb for DIC images taken with a typical camera, regardless of whether 8-bit or higher-bit images are used.
- Due to the use of interpolation to generate the raw image, Color cameras are likely to increase measurement bias and should not be used for DIC if a suitable monochrome camera is available.
- When image noise is low, the reduction in random error due to increased bit depth can be leveraged to reduce exposure time and increase the maximum sample temperature range of DIC without compromising measurement precision.

Although it was found that bit depth and exposure time can be leveraged to increase the maximum temperature range of DIC without an increase in random error, the temperature increase was relatively small for the camera and method used in this work. This increase and the effect of bit depth is dependent on image noise, however, so the difference between 8-bit and higher bit depth will vary depending on the camera used. For low-noise imaging applications, it is beneficial to use more than the standard 8 bits to capture and store images used for DIC.
REFERENCES


APPENDIX: CALCULATING IMAGE NOISE
In order to determine the proper equations to calculate and estimate image noise, a numerical study of image noise was additionally conducted to determine 1) whether quantization noise is a measured or invisible component of pixel uncertainty (invisible meaning it increases error but does not increase the standard error of the measurement); 2) the proper method to characterize typical pixel uncertainty in an image; and 3) whether image averaging reduces quantization noise. The study was divided into two parts, as follows.

The first part of the study was to determine whether quantization noise is a measured or invisible source of uncertainty and what the proper method is to characterize typical pixel uncertainty. To begin with, a ‘true’ image was created by reading an 8-bit speckle image and adding uniformly random value between ±0.5 to each pixel. This represents the true state of light intensity incident on the camera sensor (omitting variation in the actual number of photons incident on the sensor). A series of 30 ‘sampled’ images were then created by adding a known amount of normally distributed noise having standard error \( \sigma_{\text{added}} \). The sampled images represent what is captured by the camera immediately prior to quantization. These images were then converted to integer values to create ‘measured’ images. The measured images represent what is reported by the camera and stored in the computer. Using the sampled and the measured images, the standard error at each pixel was determined and attempts were made to find \( \sigma_{\text{added}} \) by averaging either the standard errors or the variances, according to Equations (24) and (25) where a bar denotes a mean and \( \sigma_I \) is the standard error of pixel intensity of a single pixel (See Eq. (22)). This process of adding noise, converting to integer-valued images, calculating measured noise based on the images, and estimating \( \sigma_{\text{added}} \) was repeated for several values of \( \sigma \).

\[
\overline{\sigma_I}
\]

\[
\frac{\sqrt{\sigma^2}}{\sigma_I}
\]  

(24)  
(25)

For the sampled images (real-valued), which equation yields the closest estimate of \( \sigma_{\text{added}} \) is the method that should be used for averaging uncertainty within an image. For the measured images (integer valued), the estimates of \( \sigma_{\text{added}} \) will show whether quantization is a measured or an invisible source of uncertainty: if the estimate of \( \sigma \) using integers is close to \( \sigma_{\text{added}} \), then quantization is an invisible source of
image noise (it does not add measurable noise to the image, but it degrades color accuracy); if the estimate of $\sigma_{\text{added}}$ is closer to $\sqrt{\sigma_{\text{added}}^2 + 1/12}$, then quantization is a measured source of image noise.

Figure 34 shows the results of the first quantization noise study. Part (a) shows $\sigma_{\text{estimated}}$ for each combination of settings (double vs integer images, Eq. (24) vs Eq. (25)) as a function of $\sigma_{\text{added}}$. The plot also shows $\sigma_{\text{added}}$ and $\sqrt{\sigma_{\text{added}}^2 + 1/12}$ vs $\sigma_{\text{added}}$ for comparison. Figure 34 (b) shows the same data but with $\sigma_{\text{added}}$ subtracted, representing the absolute error between the estimated standard error and the applied standard error. Looking first at the double images, $\sqrt{\sigma_I^2}$ is indistinguishable from $\sigma_{\text{added}}$, but $\sigma_I$ tends to be low. This means the square root of the mean variance is the correct way to estimate $\sigma_{\text{added}}$. Looking at the integer-valued images at values of sigma greater than ~0.3, both estimates follow the $\sqrt{\sigma_{\text{added}}^2 + 1/12}$ line closely with $\sigma_I$ being a little low as before. This means quantization noise is a measured portion of pixel error and once again that the variance-based approach is the correct way to calculate typical image random error. This behavior led to the use of Eq. (22) to calculate $\sigma_{\text{img}}$ in this work. It should be noted as well that as $\sigma$ approaches zero, both estimates of $\sigma_{\text{added}}$ approach zero. This divergence from the true uncertainty occurs at approximately $\sigma_{\text{added}} < \sqrt{1/12} \approx 0.29$ for the variance-based averaging method. Thus, when noise due to sources other than quantization decrease below quantization noise, quantization noise/error gradually transitions from a measured source to an invisible source of error.
Figure 34: Quantization noise study part 1 – measured vs applied image noise in real-valued (dbl images) and integer-valued (int images) images. Quantization introduces measurable noise into images. The proper way to calculate the typical standard error of pixel intensities in an image is via the square root of the mean of variances. Calculation of uncertainty for integer-valued data becomes increasingly inaccurate as uncertainty approaches zero.

The second part of the study was to determine the relationship between image averaging and quantization noise. To accomplish this, real-valued and integer-valued images with a known amount of applied noise were generated as before with $\sigma_{added} = 2. N_{avgd}$ of each of these images were then averaged together to create a mean image (real-valued, double type), stored, and then rounded to integer values and stored. This results in four total images where each image is a different combination of real-valued or integer-valued individual images and real-valued or integer-valued averaged images. This process of generating averaged images was repeated 30 times. Using these averaged images, the typical pixel uncertainty was calculated using Eq. (25). This process of generating averaged images and determining image noise was repeated for $N_{avgd} = [1,2,3,4,6,8,12,16,24,32,48,64,96,128,192,256]$ and compared to possible expected values for each. The equations for these predicted values are given by Equations (26) -
(29). Each represents a different way of how the averaged image might retain quantization noise—whether it be averaged out, and whether additional noise comes from the final conversion to an integer-valued image. Which equation matches which measured uncertainty will tell how much noise to expect in averaged images.

\[
\sqrt{\frac{\sigma^2_{\text{added}}}{N_{\text{avgd}}}}
\]

\[
\sqrt{\frac{\sigma^2_{\text{added}} + \frac{1}{12}}{N_{\text{avgd}}}}
\]

\[
\sqrt{\frac{\sigma^2_{\text{added}}}{N_{\text{avgd}}} + \frac{1}{12}}
\]

\[
\sqrt{\frac{\sigma^2_{\text{added}} + \frac{1}{12}}{N_{\text{avgd}}} + \frac{1}{12}}
\]

Figure 35 shows the results from the second quantization noise study, where predicted and measured values are laid out similarly to Figure 34. Note that what used to be \(\sigma_{\text{added}}\) on the x-axis of Figure 34 is now the predicted uncertainty according to Eq. (11) in Figure 35. Because image noise decreases as \(N_{\text{avgd}}\) increases, it is readily deduced that the \(N_{\text{avgd}} = 1\) images occur at \(\sqrt{\sigma^2_{\text{added}}/N_{\text{avgd}}} = \sigma_{\text{added}} = 2\) and \(N_{\text{avgd}}\) increases moving to the left. In the figure, the measured standard error in each type of averaged image matches closely one of the predicting equations. The exception to this is for the integer averaged, integer individual images at low numbers of \(N_{\text{avgd}}\). This behavior is explained by the \(N_{\text{avgd}} = 1\), or non-averaged, case. In this case, the averaged image is equal to the individual image, which has already been converted to an integer value; therefore the final image is equal to the non-averaged image because a second conversion to integer values will produce no change. As such, the total quantization noise is equal to \(\sqrt{\sigma^2_{\text{added}} + 1/12}\) instead of \(\sqrt{(\sigma^2_{\text{added}} + 1/12)/N_{\text{avgd}} + 1/12} = \sqrt{\sigma^2_{\text{added}} + 1/6}\), as was predicted by Eq. (29). At all other values of \(N_{\text{avgd}}\), the second quantization will introduce some amount of image noise approaching 1/12, so it is appropriate that the measured standard error be different for the case of \(N_{\text{avgd}} = 1\) and \(N_{\text{avgd}} > 1\).
Figure 35: Quantization noise study part 2 – quantization noise in image averaging. Noise in four types of averaged images is shown alongside predictions from Equations (26) - (29). Image noise predictions match closely with measured values with some deviation.

The integer-individual integer-averaged image set used in this study is analogous to the image averaging method used in other parts of this work, which means that Eq. (29) is the correct equation to predict image noise in an averaged image for this work. Substituting in $\sigma_{\text{added}}^2 + \frac{1}{12} = \sigma_{\text{img}}^2$ (See Eq. (8)) results in Eq. (12).