

Assessing the use of an infrared spectrum hyperpixel array imager to measure temperature during additive and subtractive manufacturing

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ABSTRACT

Accurate non-contact temperature measurement is important to optimize manufacturing processes. This applies to both additive (3D printing) and subtractive (material removal by machining) manufacturing. Performing accurate single wavelength thermography suffers numerous challenges. A potential alternative is hyperpixel array hyperspectral imaging. Focusing on metals, this paper discusses issues involved such as unknown or changing emissivity, inaccurate greybody assumptions, motion blur, and size of source effects. The algorithm which converts measured thermal spectra to emissivity and temperature uses a customized multistep non-linear equation solver to determine the best-fit emission curve. Emissivity dependence on wavelength may be assumed uniform or have a relationship typical for metals. The custom software displays residuals for intensity, temperature, and emissivity to gauge the correctness of the greybody assumption. Initial results are shown from a laser powder-bed fusion additive process, as well as a machining process.

In addition, the effects of motion blur are analyzed, which occurs in both additive and subtractive manufacturing processes. In a laser powder-bed fusion additive process, the scanning laser causes the melt pool to move rapidly, causing a motion blur-like effect. In machining, measuring temperature of the rapidly moving chip is a desirable goal to develop and validate simulations of the cutting process. A moving slit target is imaged to characterize how the measured temperature values are affected by motion of a measured target.

Keywords: hyperpixel array hyperspectral imager, thermography, additive manufacturing, 3D printing, subtractive manufacturing, machining, motion blur, metal parts

1. INTRODUCTION

When manufacturing metal parts, both additive (3D printing) or subtractive (machining) processes may be used. Accurate modeling of these processes depends on knowing the temperatures realized, as well as the cool-down rate since this can effect the microstructure of the resulting part. There are challenges involved when using radiation thermography to measure these temperatures¹⁻⁵. For additive processes, potential challenges include significant non-greybody behavior, small size of the melt zone, and high thermal gradients, as well as effective motion blur due to the rapid scan rate of the laser or electron beam. Motion blur can also be significant for subtractive processes when measuring chip temperature. Both processes often involve unknown, non-uniform, or rapidly changing emissivity values.

Hyperspectral imaging is a collection of methodologies which acquire images at multiple (generally three or more) optical wavelengths. In single wavelength imaging, a pixel has a scalar value representing intensity, and the camera outputs two dimensional arrays of pixels, where each pixel is a measurement of intensity at an (X, Y) location. In hyperspectral imaging, a hyperpixel is a vector of intensities as a function of wavelength. The camera outputs arrays of hyperpixels called hypercubes, thus hypercubes represent intensity as a function X, Y , and wavelength. It is in its infancy compared to single wavelength and ratiometric (two wavelength) techniques, especially for wavelengths other than visible light. Historically, its primary use has been to classify what is being imaged into categories. For example, a hyperspectral satellite image of vegetation might be classified as either forest, agricultural, or prairie. While there are researchers using more than two wavelengths for temperature measurement, hyperspectral imaging is relatively novel for thermography.

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This paper will discuss preliminary experiments performed to determine the effectiveness of using a hyperspectral camera to overcome some of the challenges encountered when measuring manufacturing process temperatures. After variables used are defined, camera hardware and software used to generate measurement results are described. Preliminary results from two known targets (a stationary blackbody and a moving slit target in front of a blackbody), as well as a subtractive process (a cutting tool) and an additive process (a laser scanning a powder bed) are presented.

2. VARIABLES AND NOMENCLATURE

Radiometric temperature measurement relies on measured radiation intensity as a function of wavelength, given by Planck's law⁶, shown in Equation 1. Equation 2 shows a modified version of Planck's law, with emissivity accounted for.

$$B(T, \lambda) = c_{1L} / [\lambda^5 * (\exp(\frac{c_2}{\lambda T}) - 1)] \quad (1)$$

$$I(T, \lambda) = \varepsilon(T, \lambda) \cdot B(T, \lambda) \quad (2)$$

$B(T, \lambda)$ Planck's law for intensity emitted by a perfect blackbody (BB), at temperature T and wavelength λ .

c_{1L} and c_2 First radiation constant ($119.1 \mu\text{W} \cdot \mu\text{m}^2/\text{sr}$) and second radiation constant ($14\,388 \mu\text{m} \cdot \text{K}$).

$I(T, \lambda)$ Intensity at temperature T and wavelength λ .

$\varepsilon(T, \lambda)$ Emissivity at temperature T and wavelength λ .

Variables associated with user input. When using the program to browse hypercubes, the graphical user interface allows the user to move a slider or select a spatial location with the mouse cursor.

S_F User selected frame number.

S_λ User selected wavelength.

C_X, C_Y User selected cartesian coordinates of an X and Y spatial location.

Variables associated with movies, images and point plots output by software.

F Frame number in a movie formed from combining sequences of hypercubes.

X, Y Cartesian coordinates of an X and Y spatial location.

I_C An intensity measured by the camera.

I_P Intensity predicted by Equation 2 which was determined by fit to measured I, λ data.

T_P Temperature predicted by Equation 2 which was determined by fit to measured I, λ data.

ε_P Emissivity predicted by Equation 2 which was determined by fit to measured I, λ data.

T_S Temperature found by solving Equation 2 when I, λ , and ε are known.

ε_S Emissivity found by solving Equation 2 when I, λ , and T are known.

For any M, N , and O , the nomenclature $M(N)[O]$ is used to designate a function $M(N)$ evaluated at slider or cursor value O . For example, $I_C(X, Y)[S_F, S_\lambda]$ is the intensity measured by the camera at location X, Y for frame S_F and wavelength S_λ .

3. CAMERA HARDWARE AND SOFTWARE

National Institute of Standards and Technology (NIST) owns the hyperspectral camera shown in Figure 1, built for NIST under contract. The camera body is physically large compared to single wavelength cameras. The camera body is temperature controlled to improve stability of the measurements. In addition, when a measurement is made a temperature controlled reference plate is also measured and used to correct for potential drift in the measurements. The camera uses an array of pinholes and a prism to acquire all wavelengths of each hypercube simultaneously at 50 hypercubes per second. The hardware for this type of camera is documented in the literature^{7,8}. Raw images from the focal plane array are shown in Figure 9. The hypercubes are 100 hyperpixel by 100 hyperpixel arrays of 11 unequally spaced wavelengths between $2 \mu\text{m}$ to $5 \mu\text{m}$. As acquired by the camera, each hyperpixel has slightly different wavelengths. To make subsequent processing easier, each hyperpixel is resampled (interpolated) to 31 wavelengths spaced $0.1 \mu\text{m}$ apart. With the current calibration, only wavelengths from $2.9 \mu\text{m}$ to $5 \mu\text{m}$ are usable. The camera was originally intended to be used for measuring subtractive processes, which typically result in surface temperatures below 700°C . The melt pool region in additive processes exhibit temperatures in excess of 1500°C , which are more

appropriately measured with wavelengths shorter than the camera is sensitive to. While not optimal for measuring additive melt pools, the camera should work well for measuring cool-down rates.

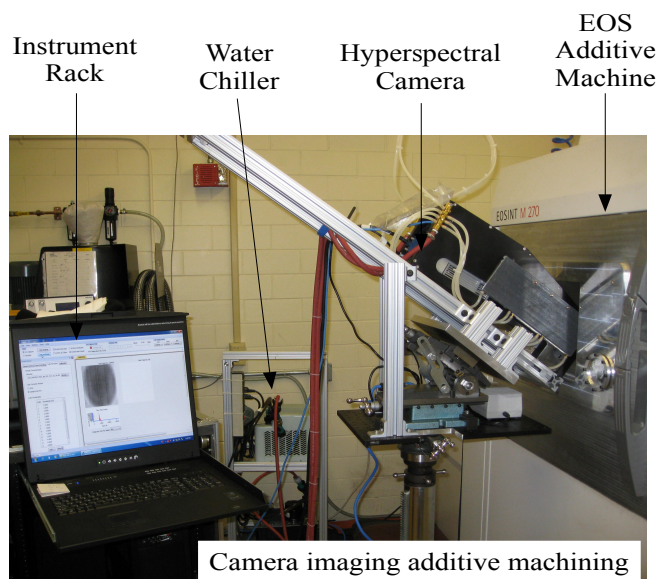


Figure 1. Camera hardware.

4. NIST SOFTWARE

The software which comes with the camera outputs a series of hypercubes (intensity as a function of X , Y , and wavelength). We are developing software for the purpose of using this information to determine temperature. It is helpful if emissivity can also be determined, or if significant deviation from greybody behavior can be detected.

Converting hypercubes to temperatures

There are two families of techniques available for converting hypercubes into temperatures. The first is classification, where the measured spectrum is compared to a database of previously measured spectra and placed into an appropriate category. For example, a particular measured spectrum could be placed in the “ $500\text{ }^{\circ}\text{C} < T < 510\text{ }^{\circ}\text{C}$ ” category. No knowledge of the underlying physics is required. However, building the data base can be very challenging.

The second family is physics based, and is generally built on Planck's law. With this family, there are two main decisions to address. First, whether to account for factors such as non-linearity in the camera, reflections from the surface, or atmospheric absorption. Our software uses Equation 2. We attempt to minimize the impact of non-linearity by using at least eight calibration points in the radiometric calibration of the camera.

The second decision is how to approach which wavelengths to use in any given situation. One approach is to select data for two wavelengths and compute temperature as you would for radiometric pyrometry⁹. You also could select several pairs and compare results as a simple estimate of measurement uncertainty. We may ultimately add this to the software. Our software currently uses all values in the measured spectrum which are above a threshold. The threshold is selected so the signal-to-noise ratio of the remaining data values are reasonable. Non-linear minimization is then used to determine values for temperature and emissivity. Residuals may be used as a simple estimate of measurement uncertainty. The hope is that using all available data (wavelengths), the best temperature estimate may be achieved. However, there are challenges with implementing this in practice. Some of these challenges are discussed next.

The software is written in Python, which includes the `scipy.optimize.minimize` suite of minimization routines¹⁰. There are three routines which support bounds, support constraints, and only require two inputs: the function to minimize and

initial estimates. However, none of these routines performed satisfactorily with our data. Some yielded reasonable outputs, but only when given really good initial estimates. Others behaved in the opposite manner, and were stable even when given poor initial estimates but tended to yield poor results. To get around this issue, we developed a multistep approach. First, a crude initial estimate of temperature is made using Wein's displacement law⁶ from the peak of the spectral intensity curve. Subsequent steps refine previous estimates using a routine which tends to improve the estimate without diverging. Another feature of the software is that the user can select weighting functions to use in the minimization process. The current composite algorithm for finding temperature and emissivity, given a spectrum (set of intensity, wavelength pairs), is as follows:

1. Find maximum value for I , as well as the value for the associated λ . Call them I_M and λ_M .
2. Use Wein's displacement law to estimate T given λ_M . Call it $T_{estimate}$.
3. Use the Planck's law to estimate I_{ideal} given $T_{estimate}$ and λ_M .
4. Set $\epsilon_{estimate} = I_M / I_{ideal}$.
5. Input $T_{estimate}$ and $\epsilon_{estimate}$ into the 'L-BFGS-B' (limited memory algorithm for bound constrained optimization, method='L-BFGS-B' in the python code) minimization algorithm as initial estimates, with all weights $W(\lambda)$ set to 1, and minimize $\sum \{W(\lambda) \{I(\lambda) - \epsilon B(T, \lambda)\}\}^2$
6. Did the user-select to limit emissivity between 0 and 1?

Yes. Input the new $T_{estimate}$ and $\epsilon_{estimate}$ estimates into the 'TNC' (Newton conjugate-gradient, method='TNC' in the python code) minimization algorithm with user-selected weighting. (TNC performs better when emissivity limits are used, but needs the very good initial estimates that L-BFGS-B with weight 1 provided in step 5.) Algorithm is now finished.

No. Is the user selected weighting 1?

Yes. Algorithm is now finished.

No. Input the new $T_{estimate}$ and $\epsilon_{estimate}$ estimates into the 'L-BFGS-B' minimization algorithm with user-selected weighting. (Some weighting functions perform poorly without the very good initial estimates that L-BFGS-B with weight 1 provided in step 5.) Algorithm is now finished.

In step 2, Wein's displacement law was used as the initial estimate. Note that below 310 °C, the maximum intensity does not yield the true peak wavelength since the long wavelength cut-off for this camera is at 5 μm . Also, above 720 °C, the maximum intensity does not yield the true peak wavelength since the effective short wavelength cut-off is about 2.9 μm for the present camera calibration. This illustrates that when using the wavelength at peak intensity to determine temperature, covering a wide range of wavelengths is needed.

The current version of the software does not fully support bad pixel detection. This is important to note when evaluating results.

Addressing emissivity dependance on wavelength

An issue to be addressed in future implementations of the software is the dependence of emissivity on wavelength. The literature shows a wide range of emissivity behavior for metals¹¹⁻¹². Over reasonable ranges of wavelength, especially for wavelengths longer than 1 μm , Equation 3 is a good approximation of $\epsilon(\lambda)$ for metal surfaces¹³.

$$\epsilon(\lambda) = A \lambda^N \quad (3)$$

Typically, N is between -0.2 and -1.1 for metal surfaces. Substituting ϵ in the present temperature conversion algorithm with $\epsilon(\lambda)$, notice that A functions in a manner similar to ϵ in the present algorithm. It is unlikely the A term will cause any numerical instability issues. However, including N adds another degree of freedom, and may potentially cause adverse effects such as converging to unrealistic values. There are two options for including N . The easiest is to allow the user to fix the value for N . The user could either select N based on a priori knowledge, or try different values to quickly see how much of a difference it actually makes in the resulting T values. A harder approach is to allow the algorithm to vary N as part of the minimization process, within bounds set by the user, and manage any numerical instability this may cause.

Displaying and summarizing results

The user adjusts frame number (S_F) and wavelength (S_λ). This causes an image representing a slice of a hypercube, defined as $I_C(X,Y)[S_F, S_\lambda]$, to update. The user may then select an X,Y location on this image (C_X, C_Y), which updates a set of images described in Table 1, as well as point plots described in Table 2.

Table 1. Images of results displayed by the software. Section 2 defines variables and nomenclature.

Intensity	Intensity Residuals	Temperature Residuals	Emissivity Residuals
$I_p(F,\lambda)[C_X,C_Y]$	$I_p(F,\lambda)[C_X,C_Y] - I_C(F,\lambda)[C_X,C_Y]$	$T_p(F)[C_X,C_Y] - T_S(I_C(F,\lambda), \epsilon_p)[C_X,C_Y]$	$\epsilon_p(F)[C_X,C_Y] - \epsilon_S(I_C(F,\lambda), T_p)[C_X,C_Y]$

Table 2. Point plots of results displayed by the software. Section 2 defines variables and nomenclature.

Temperature Summary	Emissivity Summary
$T_p(F)[C_X,C_Y]$, Average $\{T_S(I_C(F,\lambda), \epsilon_p)[C_X,C_Y]\}$, Average $\pm 2\text{StdDev}\{T_S(I_C(F,\lambda), \epsilon_p)[C_X,C_Y]\}$	$\epsilon_p(F)[C_X,C_Y]$, Average $\{\epsilon_S(I_C(F,\lambda), T_p)[C_X,C_Y]\}$, Average $\pm 2\text{StdDev}\{\epsilon_S(I_C(F,\lambda), T_p)[C_X,C_Y]\}$

Organizing hypercube data into movies

The software is able to combine two or more different series of hypercubes together to form one movie. Figure 2 shows how they may be combined in either sequential or interleaved mode. As will be discussed, superframed data is one reason for combining series of hypercubes. However, superframing is not the only reason. If series A is from one situation and series B is from a different situation, analysis of the two may be manipulated and displayed as one unit, making their comparison convenient and easy. This will be shown in Figure 5.

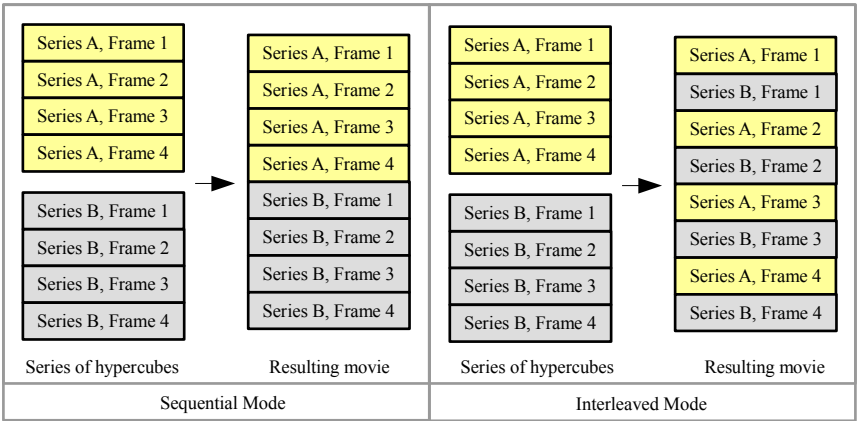


Figure 2. Comparing sequential and interleaved modes of combining series of hypercubes into a movie.

Superframing¹⁴ is a technique where the effective dynamic range of a thermal camera is extended by acquiring images at more than one integration time in an alternating manner. For example, the camera might acquire an image with an integration time of 1 μs , then 5 μs , then 1 μs , then 5 μs , and so on. Our camera supports up to 4 integration times. When a manufacturing process is imaged using superframing, data for each integration time is treated as a separate series. Thus, it is easy for the user to select which integration times to combine together into one movie. If two series are combined in sequential mode, when the movie is viewed the user will see the manufacturing process twice; once at the first integration time and then at the second integration. If combined in interleaved mode, the user will see the process once with every other frame being updated with information from different integration times.

There are several approaches available when displaying frames of interleaved results from superframed data. One approach is to simply display the frames as is. Figures 3 and 4 show two other approaches. Figure 3 shows a typical algorithm used by commercial software. Using our example where the camera acquires images with an integration time of 1 μ s, then 5 μ s, then 1 μ s, then 5 μ s, the first set of 1 μ s and 5 μ s images are combined for the first movie frame, the second set of 1 μ s and 5 μ s images are combined for the second movie frame, and so on. This movie has *NumCubesAtEachIntegrationTime* frames. However, while all pixels in a frame are displayed all at once, the frame is actually a combination of data acquired at different times. When the scene changes rapidly, users may misinterpret the movie. Figure 4 shows an alternate approach which updates each frame only with new, valid information as it is acquired by the camera. This movie has *NumCubesAtEachIntegrationTime* $\cdot$ *NumIntegrationTimes* frames.

```

Input Cubes(Inumber, Cnumber), where Inumber is the integration time number. Cnumber is the cube number.
FrameNumber = 1
FOR Cnumber = 1 to NumCubesAtEachIntegrationTime
    NextFrame(*, *) = Undefined
    FOR Inumber = 1 to NumIntegrationTimes
        CurrentCube = Cubes(Inumber, Cnumber)
        FOR X = 1 to NumPixelsInX
            FOR Y = 1 to NumPixelsInY
                CurrentSpectrum = CurrentCube(X, Y)
                CurrentResults = Process(CurrentSpectrum)
                IF CurrentSpectrum and CurrentResults pass all tests for validity
                    NextFrame(X, Y) = CurrentResults
            NEXT Y
        NEXT X
    NEXT Inumber
    MovieToBeOutput(FrameNumber) = NextFrame
    FrameNumber = FrameNumber + 1
NEXT Cnumber

```

Figure 3. Algorithm 1 for combining best parts of each integration time. This is the typical algorithm used. It produces *NumCubesAtEachIntegrationTime* frames. Each frame combines data for the *NumIntegrationTimes* integration times simultaneously, even though they were acquired at different times. When temperatures or locations change rapidly, users may misinterpret the video.

```

Input Cubes(Inumber, Cnumber), where Inumber is the integration time number. Cnumber is the cube number.
LastUpdatedFrameNumber(*, *) =  $-\infty$ 
NextFrame(*, *) = Undefined
FrameNumber = 1
FOR Cnumber = 1 to NumCubesAtEachIntegrationTime
    FOR Inumber = 1 to NumIntegrationTimes
        CurrentCube = Cubes(I, C)
        FOR X = 1 to NumPixelsInX
            FOR Y = 1 to NumPixelsInY
                CurrentSpectrum = CurrentCube(X, Y)
                CurrentResults = Process(CurrentSpectrum)
                IF CurrentSpectrum and CurrentResults pass all tests for validity
                    NextFrame(X, Y) = CurrentResults
                    LastUpdatedFrameNumber(X, Y) = FrameNumber
                ELSE
                    IF FrameNumber - LastUpdatedFrameNumber(X, Y) > NumIntegrationTimes
                        NextFrame(X, Y) = Undefined
            NEXT Y
        NEXT X
    NEXT Inumber
    MovieToBeOutput(FrameNumber) = NextFrame
    FrameNumber = FrameNumber + 1
NEXT Cnumber

```

Figure 4. Algorithm 2 for combining best parts of each integration time. Produces *NumCubesAtEachIntegrationTime* $\cdot$ *NumIntegrationTimes* frames. Updates the video in a way which more accurately represents when the data was acquired.

5. RESULTS FROM PRELIMINARY EXPERIMENTS

Blackbody data

First, we will look at blackbody (BB) data. The intent is to look at data where we know the correct answer so we may determine how well the software converts hypercubes into temperature and emissivity values. No bounds were imposed on emissivity. There are five BB temperatures, 140 °C, 250 °C, 330 °C, 402 °C, and 600 °C. At each temperature, 100 hypercubes were measured. These were combined using the sequential mode to create a 500 frame movie. Figure 5 shows results for one typical X,Y location in an image of the BB processed in the normal way, in which both temperature and emissivity are calculated. Note the intensity residuals are typically about 5% of the intensities.

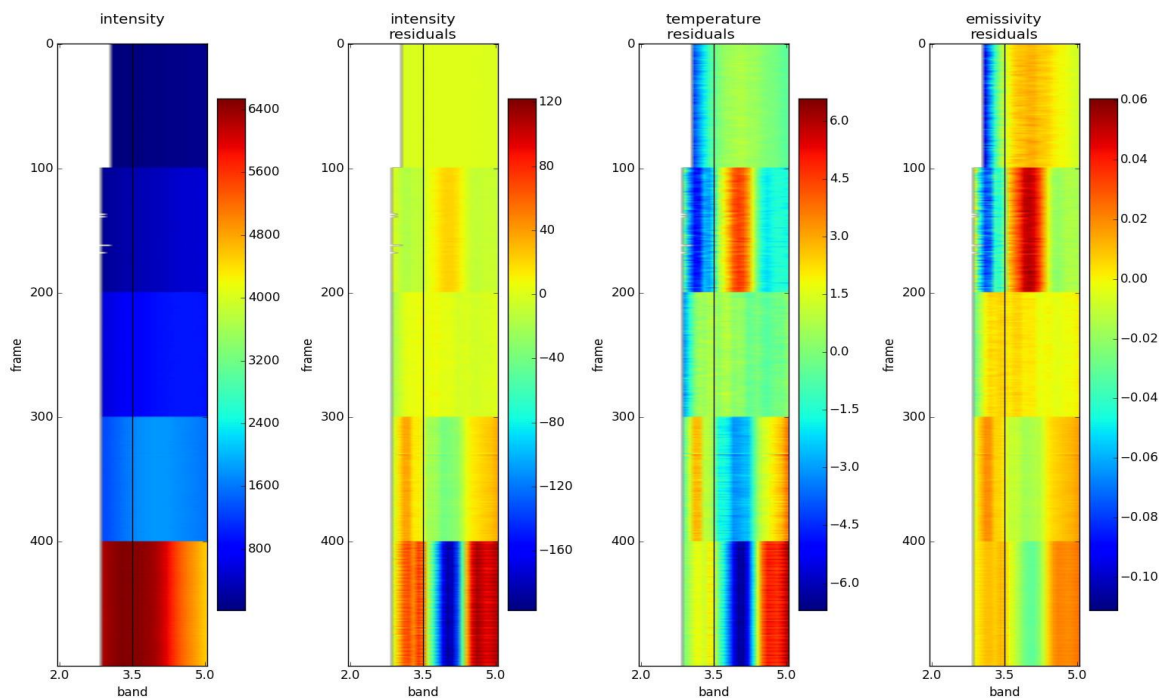
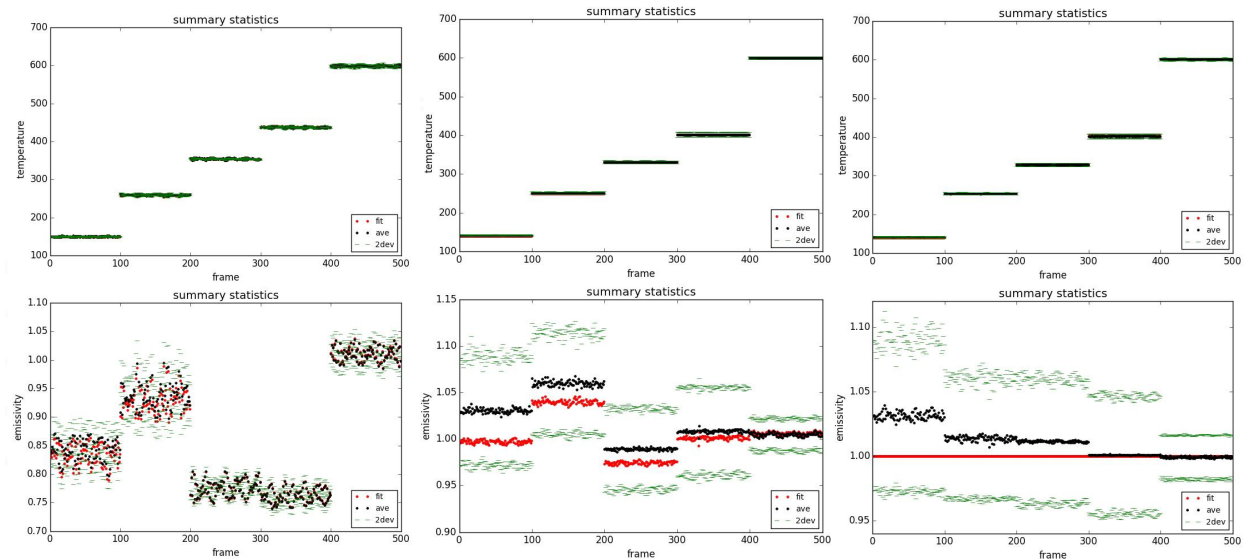


Figure 5. Results for five BB temperatures. The wavelength band (in μm) for each plot go across the bottom. Temperatures are in °C. Table 1 defines these plots. Frame number in the movie goes from the top of the figure toward the bottom.

Figure 6 shows point plots of the same data, but processed three different ways. 1)The normal way, where the software must solve for both temperature and emissivity values. 2)Set temperature values to the BB temperatures so the software only has to solve for emissivity. 3)Set emissivity values to 1 so the software only has to solve for temperature. While emissivity of the BB is actually closer to 0.98, it was treated as 1 in the calibration procedure, so emissivity set to 1 is appropriate here.

Note that when the temperature or emissivity value is set, T_p or ε_p is set, which is not directly wavelength dependent. However, residuals include T_s or ε_s , which are wavelength dependent. If there are W wavelengths, each T_p or ε_p will result in W non-zero residuals.



Normal mode, software solves for both T and ϵ . Set T to BB temperature, solved for ϵ . Set ϵ to 1, solved for T .

Figure 6. Results for five BB temperatures. Table 2 defines these point plots. Temperatures are in $^{\circ}\text{C}$. The green bars are ± 2 standard deviations.

Results from Figure 6 are summarized in Table 3. Looking at the section where both T and ϵ are solved for, errors in T are generally about 10% too high while errors in ϵ are generally about 10% too low. In the other two sections of the table, only one variable is being solved for. In these cases, errors are significantly smaller, generally about 1% or less.

Table 3. Summary of data in Figure 6. Temperatures are in $^{\circ}\text{C}$.

BB Temp	Normal mode. Solve for both T and ϵ .				Force T to BB temperature. Solve for just ϵ .				Force ϵ to 1. Solve for just T .			
	Ave(T_p)	Ave(Ave(T_s))	Ave(ϵ_p)	Ave(Ave(ϵ_s))	Ave(T_p)	Ave(Ave(T_s))	Ave(ϵ_p)	Ave(Ave(ϵ_s))	Ave(T_p)	Ave(Ave(T_s))	Ave(ϵ_p)	Ave(Ave(ϵ_s))
140	149.7	150.1	0.83	0.84	140	141.2	1.00	1.03	140.0	141.1	1	1.03
250	259.2	259.6	0.93	0.94	250	251.0	1.04	1.06	253.3	253.9	1	1.01
330	354.4	354.4	0.78	0.78	330	330.8	0.98	0.99	327.9	328.2	1	1.01
402	437.7	437.5	0.76	0.76	402	401.9	1.00	1.01	402.9	402.1	1	1.00
600	599.0	598.5	1.01	1.01	600	599.6	1.01	1.01	601.2	600.9	1	1.00
Difference from expected value												
140	09.7	10.1	-0.17	-0.16	0	1.2	0.00	0.03	0.0	1.1	0	0.03
250	09.2	09.6	-0.07	-0.06	0	1.0	0.04	0.06	3.3	3.9	0	0.01
330	24.4	24.4	-0.22	-0.22	0	0.8	-0.03	-0.01	-2.1	-1.8	0	0.01
402	35.7	35.5	-0.24	-0.24	0	-0.1	0.00	0.01	0.9	0.1	0	0.00
600	-1.0	-1.5	0.01	0.01	0	-0.4	0.01	0.00	1.2	0.9	0	0.00
Ave Diff	15.6	15.6	-0.14	-0.13	0	0.5	0.00	0.02	0.6	0.8	0	0.01

Subtractive manufacturing; chip and cutting tool

Next, machining of metal workpieces will be examined. Ideally the tool surface is flat, and emissivity changes little from a known value during machining. However, independent emissivity measurement and surface preparation to prevent oxide formation during testing can be time consuming. For this study, the side of the tool was simply ground flat. Values for emissivity at different locations were independently measured for two tools prepared in this way. Emissivity averaged 0.4 and ranged from 0.2 to 0.6. Also, when the only tool preparation is to grind the side of the tool, oxides can form during cutting tests due to elevated temperatures, which cause emissivity to increase.

Figure 7 shows an attempt to measure chip temperature during machining. The cutting conditions were a surface speed of 60 m/min and a feed rate of 0.28 mm/rev. This is Test 6 from a set of tests measuring cutting forces for an additively

made workpiece¹⁵. The workpiece was additively made of EOS GP1 powder, nominally equivalent to 17-4 stainless steel. It was 4.24 mm thick, and was centered over the cutting tool with the camera-facing side of the disk 0.66 mm from the camera-facing side of the tool. Superframing was used using two integration times, 2.5 ms and 0.2 ms. Field of view is about 19 mm wide. During cutting, the chip occasionally curled back and obscured the camera view, so some frames of the movie must be ignored. Ideally, a higher magnification would be better since the chip is only a few hyperpixels wide. The chip measures about 550 °C during cutting, which is reasonable for these cutting conditions. Due to compliance in the fixturing, the tool slowly moves as cutting force changes, complicating interpretation of the data. Image tracking may ultimately be added to the software to keep the cursor on the desired feature.

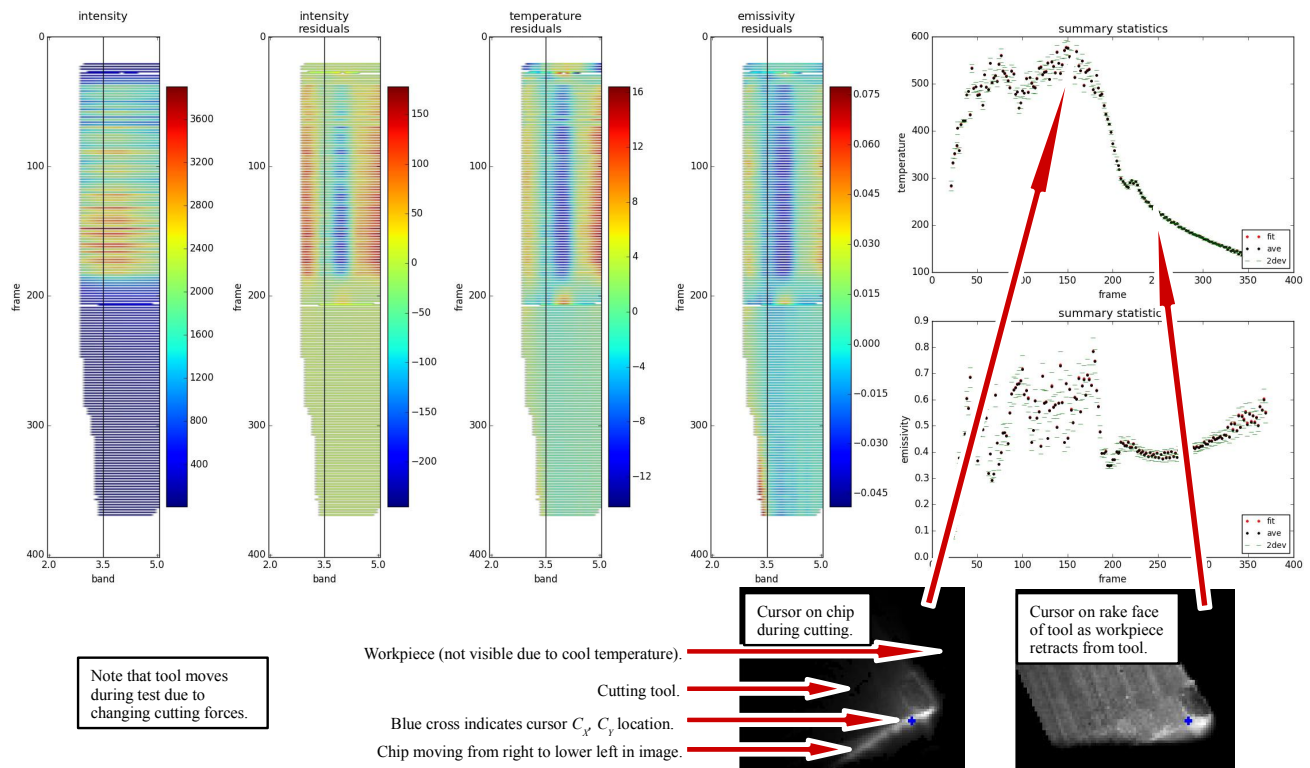


Figure 7. Measuring chip temperature. Temperatures are °C. Field of view is about 19 mm wide. The green bars are ± 2 standard deviations.

Figure 8 shows the same test, but with the cursor in different locations. Ignoring outliers due to the chip occasionally obscuring the view, the workpiece material stuck to the side of the tool peaked at about 500 °C. Emissivity is about 0.25 and may have increased to 0.4 due to oxidation. However, more experience with the camera system is needed before the authors are willing to attribute the entire change in emissivity due to oxidation. The tool near the stuck material peaked at about 445 °C. Emissivity is about 0.35 and may have increased to 0.55 due to oxidation. The body of the tool well away from the chip peaked at about 240 °C. Emissivity is about 0.3 and may have increased to 0.35 due to oxidation.

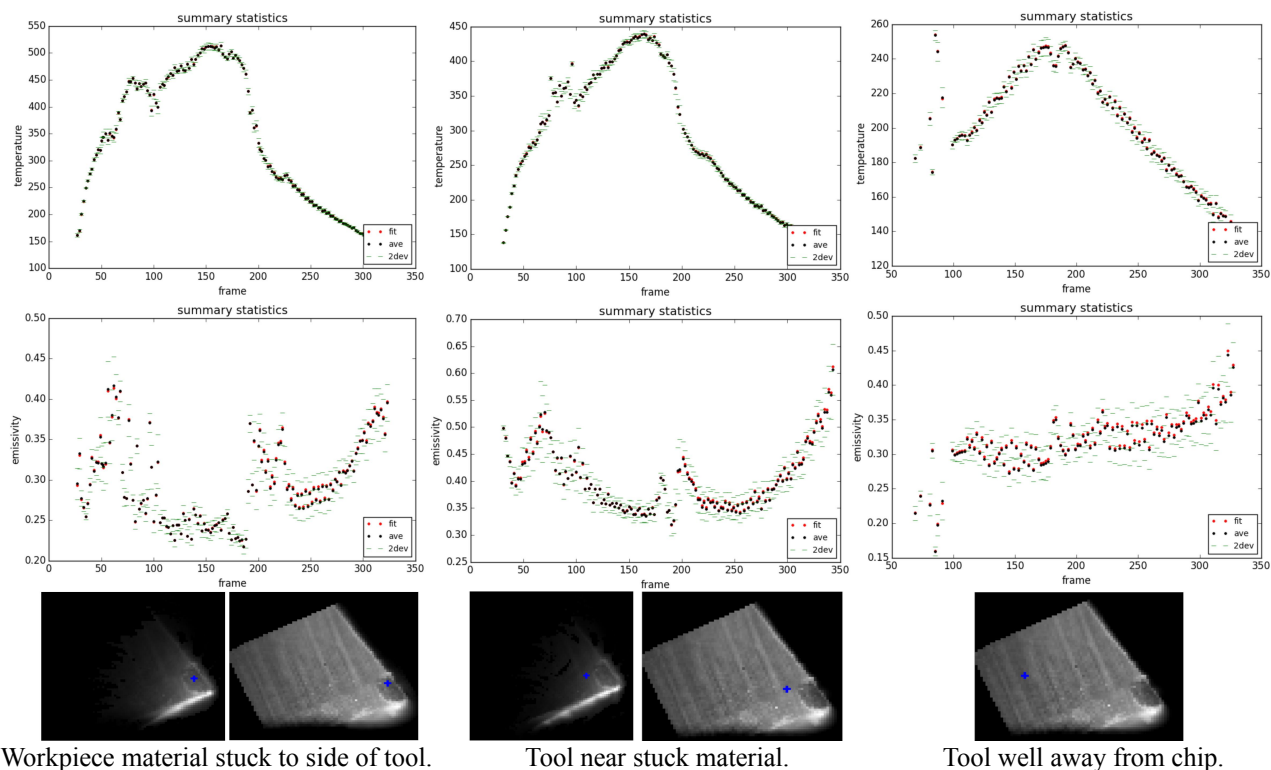
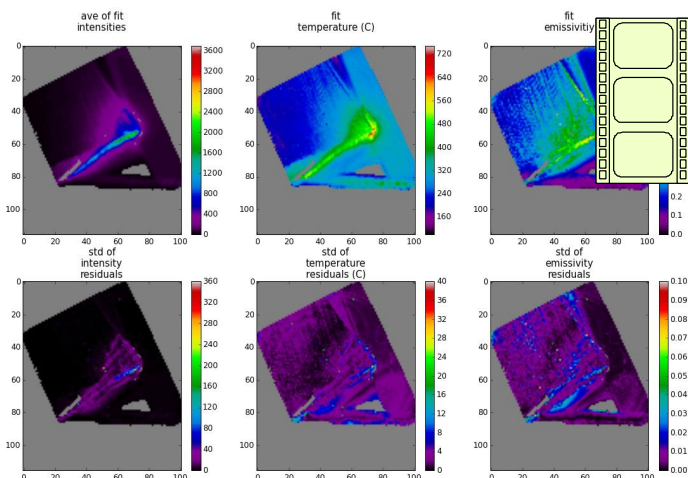


Figure 8. Looking at different locations on the tool. Temperatures are °C. The green bars are ± 2 standard deviations. Field of view is about 19 mm wide. During cutting, the chip occasionally curled back and obscured the camera view, so some frames of the movie must be ignored.

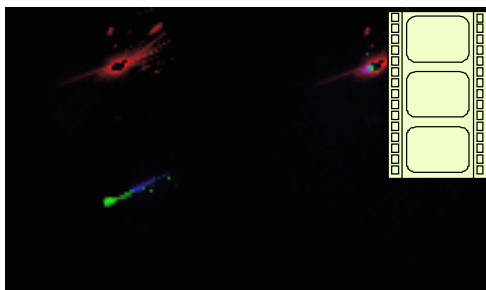
A similar analysis may be performed at every X,Y location, and calculated temperature or emissivity values plotted as a sequence of images. Video 1 is an example for this cutting test. The top row of images show The algorithm shown in Figure 4 was used to update the frames.



Video 1. Video of results for cutting test. Temperatures are in °C. Field of view is about 19 mm wide. During cutting, the chip occasionally curled back and obscured the camera view, so some frames of the movie must be ignored. Available for download at <http://dx.doi.org/10.1117/12.2222575>

Additive manufacturing; laser scanning of a metal powder bed

Due to the small laser spot size, combined with the long lens-to-subject distance, available lenses could not achieve a satisfactory magnification. NIST subsequently acquired a custom made 100 mm focal length lens, which should provide a 1:1 magnification at the 200 mm lens-to-subject distance required. This will be used in future work. Nevertheless, the present data is illustrative of using superframing to capture the wide range of rapidly changing temperatures inherent in this process. To make the three integration times easy to differentiate in the movie, intensities for one wavelength were selected and color coded in the images: red for 100 μ s, green for 10 μ s, and blue for 1 μ s. Saturated pixels are set to undefined, so the red areas appear to have holes in them. The laser scanned a square path, which looks rectangular due to the camera viewing angle. Video 2 shows the scan using the algorithm shown in Figure 4 on the left of the frame, as well as the algorithm in Figure 3 on the right. The algorithm in Figure 4 does a much better job of showing when the data was actually acquired. While the metal powder does not move, Video 2 illustrates that the “hot spot” moves very rapidly. Thus, there is effectively a motion blur which may potentially affect the accuracy of temperature measurements.



Video 2. Video of laser scan. Superframing using three integration times was used. Each integration time is color coded red, green, and blue. Combined using the algorithm in Figure 4 (on the left), as well as the algorithm in Figure 3 (on the right). Available for download at <http://dx.doi.org/10.1117/12.2222575>

Blackbody imaged through a moving slit; characterizing effects of motion on temperature measurements

With single wavelength cameras, the effect of motion blur may be modeled and sometimes compensated for³. However, this is not true for the hyperspectral camera. To better understand the effect of motion, a chopper wheel was placed in front of a 210 °C BB whose aperture size was set to 2.54 mm. The camera acquired data with an integration time of 2.5 ms. Two wheel speeds and three wheel angles were used. In addition, measurements were made as the camera came to thermal equilibrium to determine how long to wait after turning the camera on, before one should take measurements.

Figure 9 shows results for one X,Y location in the center of the BB aperture. Example raw images from the camera focal plane array are included. There are arrays of small stripes on the images. Each stripe is a spectrum to be converted into a hyperpixel by the camera software. Three slit angles, relative to those stripes, are shown: 0 degrees, 45 degrees, and 90 degrees. Two wheel speeds are shown, 101 slits per second and 999 slits per second. At 101 slits per second, an apparent rise in temperature is seen as the slit blocks the BB for part of the integration time, a level area where the BB is exposed the entire integration time, and an apparent drop in temperature as the slit blocks the BB for part of the integration time. When the intensity is below a set threshold, temperature is set to undefined. Ideally, temperature would always be either the BB temperature or undefined, with emissivity values fluctuating as a result of effective motion blur. When the threshold was set high enough that the rising and falling temperature values disappear, much of the usable range of the camera is lost. At 999 slits per second, the BB was always blocked during part of the integration time. The size of this effect is about the same for all angles tried, indicating that the effect of motion blur is about the same for all directions. Looking at just the level portion of the 101 slits per second data, measured temperatures were about 15 °C too high 30 minutes after the camera was turned on, but came within 5 °C after about an hour.

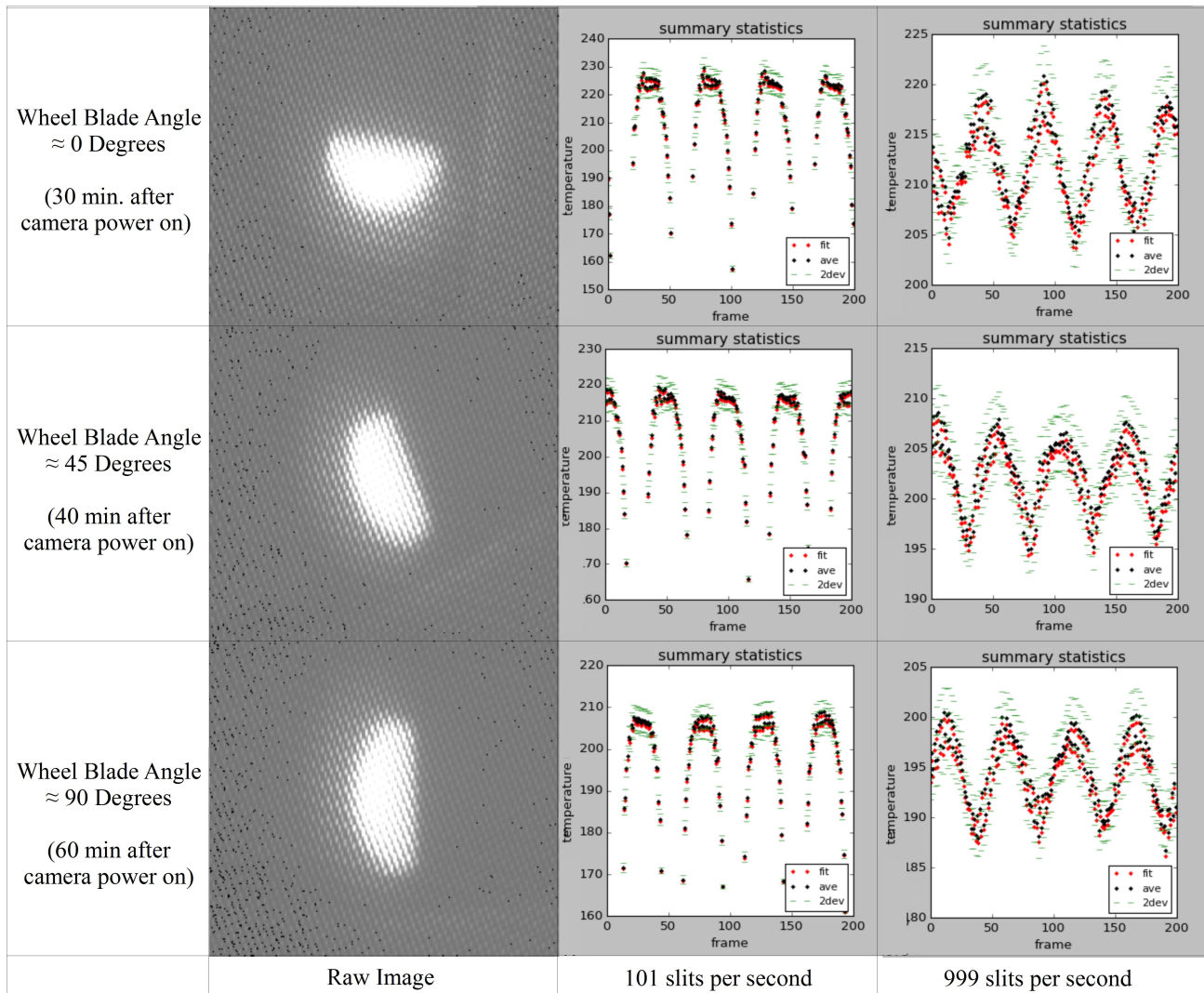


Figure 9. Experiment to understand effect of motion blur, as well as how long it takes for the camera to stabilize after being turned on. Temperatures are $^{\circ}\text{C}$.

6. CONCLUSION

Four types of images were examined to determine the strengths and weaknesses of the NIST hyperspectral camera: a subtractive manufacturing process tool and chip, a laser powder bed fusion additive manufacturing process, a stationary blackbody, and a moving slit in front of a blackbody. Based on these results, we draw the following conclusions.

1. As long as there are no size of source issues or motion blur issues, the camera gives reasonable estimates of temperature, as well as emissivity.
2. Both actual motion as well as apparent motion due to rapidly changing temperature gradients affect the accuracy of temperature measurements. Other models, such as radiometric or a classification scheme, can be added to the software to see if temperature estimates improve.
3. Future work includes implementing the $\epsilon(\lambda)$ function optimized for metals, as outlined in this paper.
4. Having an appropriately high magnification is important. Future work includes redoing the experiments described in this paper with the new higher magnification lens.

5. Additive manufacturing produces a very wide range of temperatures. Both single wavelength and hyperspectral cameras have dynamic ranges which can not measure all temperatures desired. Thus, either superframing, the use of multiple cameras, or repeat tests with the camera set to different parameters are likely required.
6. Certain characteristics of the camera are fixed and not easily changed, such as the number of wavelength bands, number of hyperpixels, and wavelength range. However, different situations are optimized by different characteristics. For example, measuring the melt pool in an additive process is best performed using wavelengths in the 0.9 μm to 1.7 μm range while measuring cool-down temperatures are better performed using longer wavelengths. A camera design which allows the characteristics to be changed more easily would greatly enhance the utility of such cameras.
7. This camera has a slow frame rate, 50 hypercubes per second, compared to a laboratory grade single wavelength camera which typically achieves hundreds or thousands of frames per second.

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