

Invited: Error Estimation for Unsteady Pressure Sensitive Paint Measurements

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The Unsteady Pressure Sensitive Paint (uPSP) team at NASA Ames uses the lifetime method to measure steady pressures and the intensity method to obtain the unsteady (fluctuating component) of pressure. As with any measurement, it is also important to understand the associated levels of uncertainty. This paper presents a method to propagate the main error sources through the working equations for steady and unsteady pressure measurements, for both the lifetime method and intensity method, and generate uncertainty estimates. Having such estimates is important for test planning purposes and for data quality checks. Two forms of errors are considered. Random error originates mostly from shot noise and read noise inherent in the camera system and manifests as a root-mean-square error in steady pressure measurements or a noise floor in power spectral densities generated from unsteady pressure measurements. Bias error originates mostly from uncertainties in surface temperature and paint calibration and is observed as an offset relative to static pressure tap and pressure transducer measurements. These error sources are discussed, including the behavior of the cameras and the paint, and a tool for estimating error is developed. This estimation method is then compared to measurements from pressure transducers obtained in the Launch Vehicle Demo Test (LVDT), a large scale uPSP wind tunnel test performed in the Ames 11-Foot Transonic Wind Tunnel.

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I. Introduction

Compared to discrete pressure transducers, Unsteady Pressure Sensitive Paint (uPSP) can provide full model coverage, resulting in a rich dataset that can be analyzed in a wide variety of ways. However, noise is an ever-present issue in these measurements. When power spectral densities from uPSP are compared to those from pressure transducers ('Kulites') the uPSP will often demonstrate an obvious noise floor depending on tunnel conditions and the resulting signal to noise ratio. This noise floor is affected by the characteristics of the paint calibration, the

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illumination level, and camera noise characteristics. Because this is a major limitation on the applications of uPSP, a method of estimating the noise floor for test planning purposes and for real-time data quality checks is desirable. An analytical method of performing this estimation is developed in this paper. The relevant noise characteristics of the cameras (Phantom v2512), the paint response (ISSI Porous, Fast-Response Pressure Sensitive Paint), and the propagation of error through the PSP working equations are considered and a formula for noise floor estimation is obtained. This is then expressed in the form of two plots, which can be used together to look up an estimated noise floor given a mean camera grey level ('Digital Number', or also 'counts'), spatial averaging size, temperature, and steady pressure. These plots also provide an intuitive understanding of the behavior of the noise floor with varying conditions. Data obtained from the recent Launch Vehicle Demo Test (LVDT) performed in the Ames 11-Foot Transonic Wind Tunnel [1] is used to demonstrate this tool. Both laboratory paint calibration data using an ISSI CAL-04 paint calibration chamber and in-situ pumpdown paint calibration data from the LVDT test are used.

II. Analysis

The analysis detailed in this paper progresses through the items listed below.

- Camera noise
 - Fixed Pattern Noise (FPN), including Dark Signal Non-Uniformity (DSNU) and Photoresponse Nonuniformity (PRNU)
 - Periodic Noise, characterized by time-varying patterns
 - Random Noise, dominated by shot noise and read noise
- Paint Response
 - Pumpdown paint calibration and paint modeling
 - Spatial nonuniformity
- PSP Processing
 - Propagation of errors through the PSP working equations

The random noise sources are handled quantitatively and propagated through to a noise floor in the resulting sound pressure level. The bias error sources are considered qualitatively, but an understanding of them is still important for interpreting the results. The main product of this analysis is presented in the form of two graphs – a plot of noise floor vs. counts for a reference condition (68°F and 2116 psf) and a contour plot used to adjust that noise floor for non-reference temperature and pressure. These tools can be used to estimate noise floor given a brightness level (in camera grey level, or counts) or alternatively to determine the required counts for a desired noise floor.

A. Camera Noise Sources

It is desired that in the absence of light, each pixel will record the same nonzero 'black level'. The discrepancy between this desired black level and the actual value in counts is called the Dark Signal Non-Uniformity (DSNU). To correct for DSNU, an offset value is applied to each pixel that will result in a reading of the correct black level when no illumination is present. DSNU is affected by sensor temperature and exposure time. Phantom v2512 has a "Current Session Reference" (CSR) feature which closes a mechanical shutter, takes dark images, and uses that data to calculate new DSNU correction offsets. In our uPSP system, a CSR is performed after every recording in preparation for the next recording. However, this process is not perfect and some residual DSNU is still apparent. It is also more apparent when the camera's sensor temperature has changed due to instrument warmup or changing environmental conditions in the wind tunnel. Beyond the built-in camera CSR feature, no additional steps are taken in order to correct for DSNU. However, understanding the typical DSNU patterns is helpful when interpreting processed results.

The conversion factor from photoelectrons to counts is known as the gain. This gain will vary slightly between pixels - this variation is called Photo Response Non Uniformity (PRNU). In addition, the gain also nonlinear, meaning that it varies slightly with illumination level. In pressure sensitive paint measurements, the quantity of interest is usually a ratio between two images rather than a single image. If gain were constant with illumination any pixel-to-pixel variation in gain would cancel itself out in the ratio. In practice this is largely true, but the slight variation of gain with illumination level results in PRNU related artifacts. This is illustrated in Figure 1 below.

These sources of fixed pattern noise generate undesired artifacts in the data products. A more comprehensive review of these factors can be found in the EMVA 1288 standard [2]. The flatfield correction process described in Ref. [3] is helpful in addressing these artifacts.

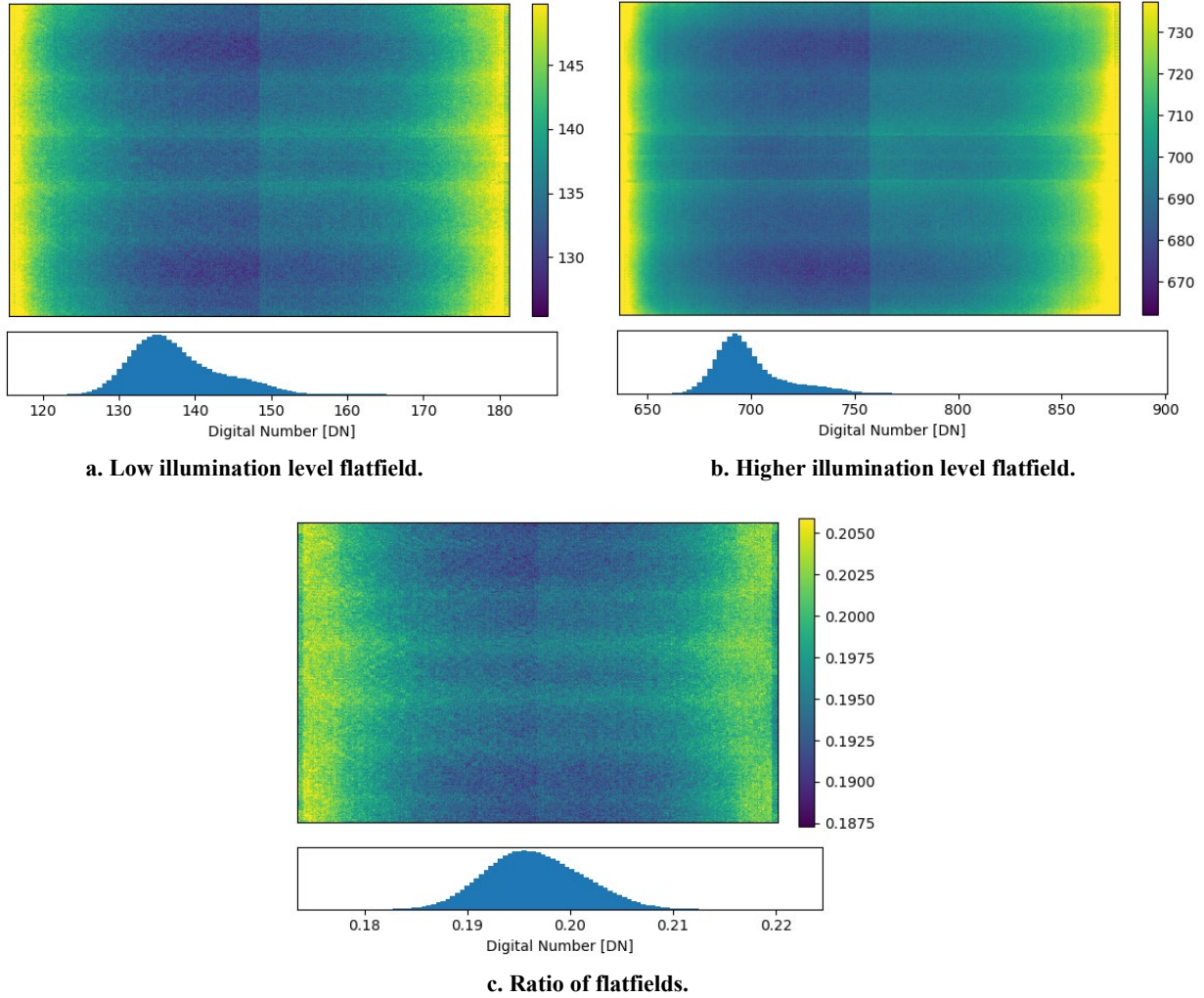


Figure 1: Representative flatfield images and flatfield image ratio showing typical PRNU pattern. The illumination levels are chosen to be representative of lifetime PSP data.

In addition to DSNU and PRNU, which are static in time, periodic noise appears as a time varying pattern overlaid onto the data. In our particular system, this sometimes appears as diamonds propagating across the image. Thus, the power spectrum of a static flat field can show sharp spikes in the frequency domain. This noise will propagate into final PSP results, especially into power spectral density plots. In the future, a frequency domain notch reject filter may be used to filter out this noise.

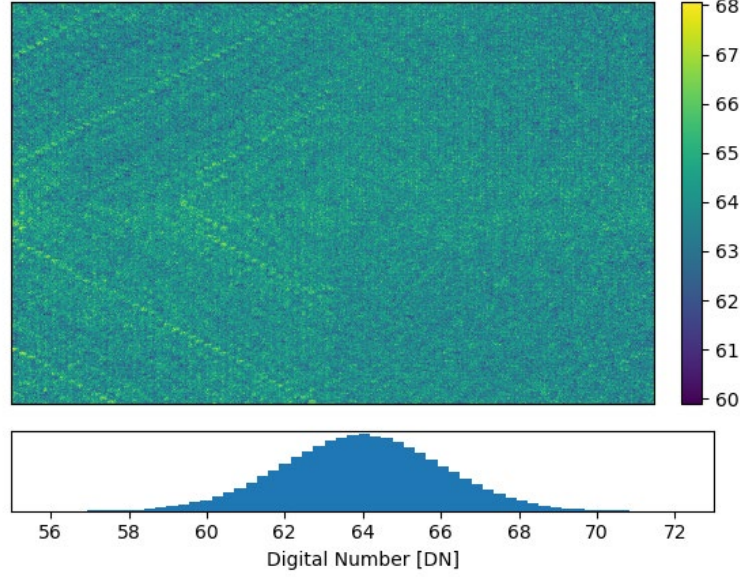


Figure 2: Dark field image taken at typical acquisition settings (20 kHz frame rate, 45 uS exposure) with shutter closed, displaying time varying pattern noise on left quadrants. Camera black level is 64 DN.

Two main sources of random noise are considered in this analysis. These are read noise and shot noise. Due to the short exposure times involved, dark current noise is not considered. These noise sources define the noise floor of the uPSP measurements. Read noise is generated by the readout electronics on the camera and is characterized with a constant variance independent of signal level. Shot noise is generated by the discrete nature of photons and is characterized with a Poisson distribution, where the variance is equal to the mean. The noise sources can be treated as uncorrelated between pixels, and as such their effect can be reduced by averaging multiple pixels together. This is further discussed in the PSP Processing section.

B. Paint Response

The Stern-Volmer relationship models the kinetics of the PSP quenching process as follows [4]:

$$\frac{I_0}{I} = \frac{\tau_0}{\tau} = 1 + KP = 1 + k_q e^{-\frac{k_T}{T}} \tau_0 P$$

Where I indicates luminescent intensity, τ the luminescence time constant, K the rate coefficient, P the pressure, and the subscript $_0$ indicates vacuum (zero pressure) conditions. In this paper, K is assumed to follow an Arrhenius temperature dependence. Thus, K is then the product of a constant k_q , an exponential term involving the temperature dependence parameter k_T , and the vacuum luminescence time constant.

It has been observed that this linear model does not adequately fit our measured paint responses, neither in the laboratory calibration chamber nor during wind tunnel wind-off pumpdowns. The observed intensity ratio I_0/I is not linear with pressure. This is illustrated in Figure 3 below which was generated using data obtained in a laboratory calibration chamber. The linear best fit lines deviate significantly from the experimental data points (notated with markers), particularly at higher temperatures.

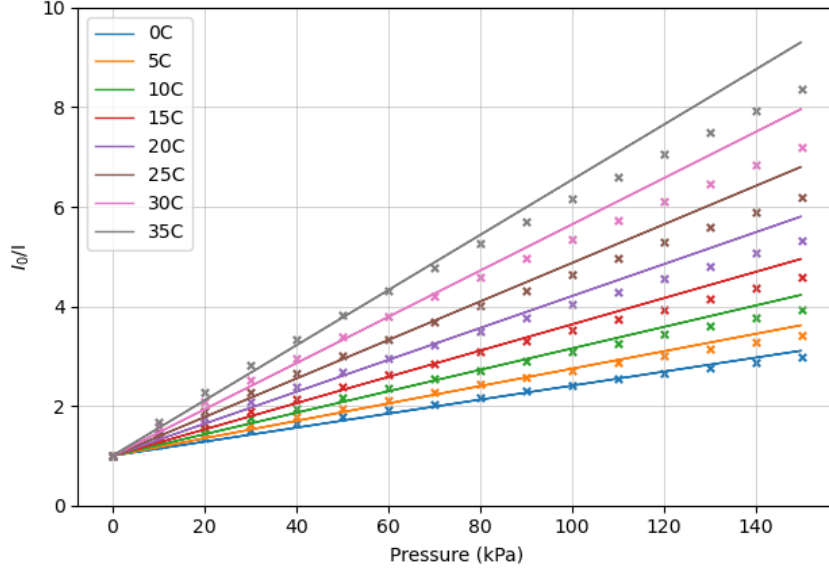


Figure 3: Linear Stern-Volmer fit to laboratory calibration data.

$$k_q = 793 \text{ kPa}^{-1} \mu\text{S}^{-1}, \quad \tau_0 = 3.08 \mu\text{S}, \quad k_T = 3296 \text{ K}$$

It was found that modeling the paint as a superposition of two independent Stern-Volmer relationships, referred to here as Response A and Response B, improves the quality of the fits. The form of this two-response paint model is shown below.

$$I = \frac{I_{0A}}{1 + k_{qA} e^{-\frac{k_T}{T}} \tau_{0A} P} + \frac{I_{0B}}{1 + k_{qB} e^{-\frac{k_T}{T}} \tau_{0B} P}$$

$$\tau_A = \frac{\tau_{0A}}{1 + k_{qA} e^{-\frac{k_T}{T}} \tau_{0A} P}$$

$$\tau_B = \frac{\tau_{0B}}{1 + k_{qB} e^{-\frac{k_T}{T}} \tau_{0B} P}$$

The observed luminescent intensity I (the value attained by the paint after several paint time constants) is simply the sum of the luminescent intensities of the two responses. It is also important to note that the time response of the luminescence involves the superposition of two independent first order responses and thus cannot be characterized by a single time constant. Also, the time constants τ_A and τ_B are not directly measured with our high-speed camera. Instead, the Gate 1 exposure integrates over the first 45 microseconds after lamp excitation starts, and Gate 2 integrates over the 45 microseconds after lamp excitation ceases. The ratio Gate2/Gate1 is called the lifetime ratio, denoted R_L . The mathematical model of two superimposed first order responses is used to fit this data and obtain the time constants. Figure 4 shows a two-response model fit to the same data shown in Figure 3. It can be seen that the accuracy of the fit is significantly improved.

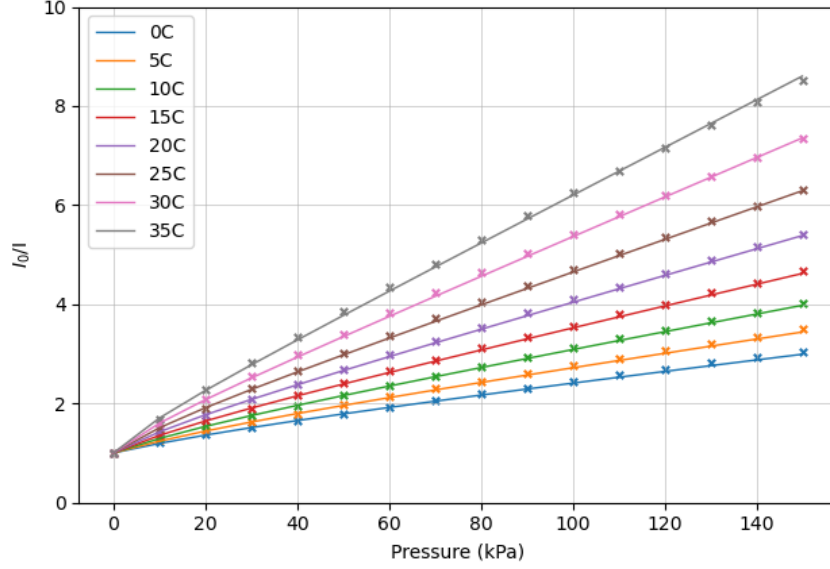


Figure 4: Two response Stern-Volmer model fit to laboratory calibration data.

$$\begin{aligned}
 I_{0A} &= 0.52, & k_{qA} &= 1048 \text{ kPa}^{-1} \mu\text{S}^{-1}, & \tau_{0A} &= 2.79 \mu\text{S}, \\
 I_{0B} &= 0.48, & k_{qB} &= 2504 \text{ kPa}^{-1} \mu\text{S}^{-1}, & \tau_{0B} &= 6.47 \mu\text{S}, & k_T &= 3552 \text{ K}
 \end{aligned}$$

This model is clearly superior to a simple linear model. In addition, this approach is preferable to using a look up table or high order polynomial fit for several reasons. Expressing the paint calibration in terms of parameters with physical interpretations is helpful for understanding and troubleshooting. But more importantly, this also reduces the number of data points required to produce an adequate fit. Reducing the number of wind-off pumpdown data points is desirable from a wind tunnel productivity perspective, and a reasonable number of pumpdown points is probably less than ten. A high order polynomial fit of adequate quality may require many more pumpdown data points, which may be impractical to acquire in a production wind-tunnel environment and instead must be done in an external laboratory calibration. Such an external calibration is performed on a paint coupon and not the model itself, which in our experience may behave differently. It is also not possible to cover the full expected temperature and pressure range with pumpdown data, and as such extrapolation outside of the calibration will be required. A polynomial fit that does not incorporate an underlying physical model would likely not perform well when extrapolating.

By using in-situ pumpdown data, it is also possible to generate spatially varying paint calibrations. This addresses spatial nonuniformity of the paint response directly. Figure 5 shows the spatial variation of model parameters obtained from LVDT pumpdown data, showing a small, zoomed in portion of the wind tunnel model. Two simplifications to the paint model were made – setting k_{qB} equal to zero (and thus $\tau_B = \tau_{0B}$, independent of pressure) and using an assumed value for k_T . These simplifications were justified by the following observations. When performing fits to this data, it was found that Response A follows the Stern-Volmer model while Response B has very little pressure sensitivity (or alternatively, has a Stern-Volmer constant of zero and therefore represents luminescence with no quenching involved). Both responses were also found to have very similar Arrhenius temperature dependence constants. Removing these two fit parameters also significantly decreased the computational expense of performing an independent paint calibration for every pixel.

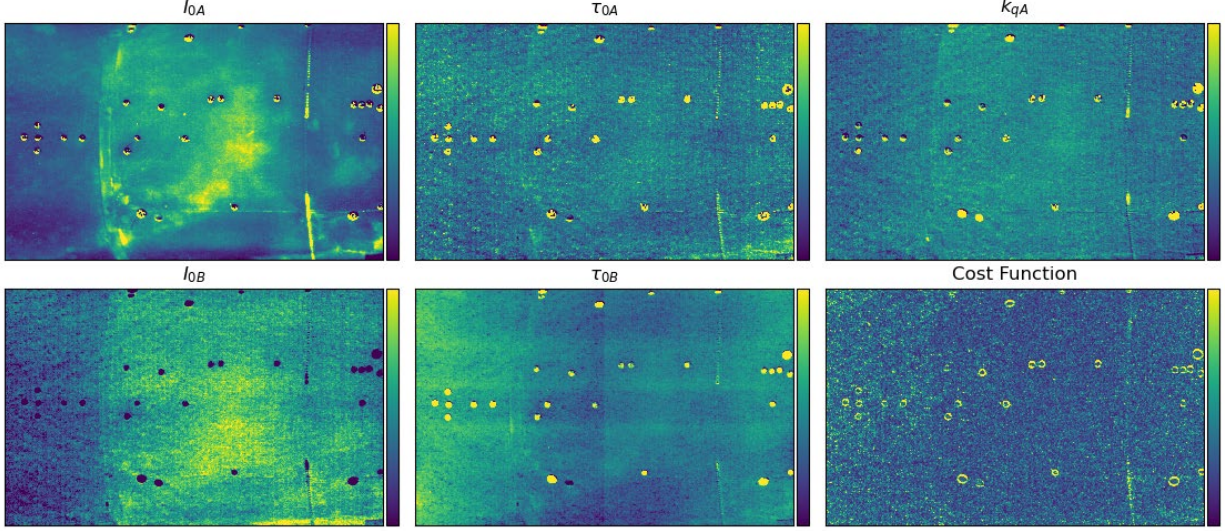


Figure 5: Spatial variation of fit parameters for sample LVDT pumpdown data.

In Figure 5, fiducial marks and pressure transducers are not painted and appear in the images as circles. A line of trip dots was applied on the right and appear as bright vertical lines of pooled paint. Apart from these artifacts, the rest of the image can be interpreted as characteristics of the paint. Some unevenness of the paint application can be seen, especially in a crescent across the center. The paint unevenness is most apparent in the I_{0A} image, but the same overall spatial variation in parameters can be discerned in the other images as well. All of this indicates that the paint calibration varies over the model, and that the variation is captured by this pumpdown calibration method.

However, it is also apparent that some characteristics of the previously described noise (PRNU and pattern noise) are visible in the fit parameters. τ_{0B} is particularly affected by PRNU, exhibiting the pattern previously seen in Figure 1. The fitted parameters are to some degree correcting for these camera noise characteristics. This anticipated to cause errors if there is model motion. In future work, an additional flatfielding process will be applied to reduce the amount of fitting to camera noise that occurs. The flatfield correction process used in Ref [3] can be used for this purpose.

C. PSP Processing

The noise characteristics for each of the Phantom v2512 high speed cameras used by the uPSP group were measured through a flat field calibration process. Representative values were obtained for both the camera gain (defined here as the number of incident photons that result in one digital count) and read noise variance as 0.25 photons per count, and 25 counts², respectively.

Shot noise (in photons) is modeled with a Poisson distribution, which has the property that the mean is equal to the variance. Multiplying that quantity by camera gain results in shot noise in counts. Using this property, the variance of the shot noise component of noise is obtained using the equation below.

$$Var(DN_{shot}) = Var(G_c I_{shot,photons}) = G_c^2 Var(I_{shot,photons}) = G_c DN_{mean} \quad (1)$$

Where DN is pixel counts, G_c is the pixel gain, and $I_{shot,photons}$ is the photon flux. Thus, the variance due to shot noise can be approximated as the pixel gain multiplied by the mean counts.

In the intensity method, the fluctuating component of pressure is obtained using the equation below [5].

$$\Delta P = G_p \left(\frac{DN_{mean}}{DN} - 1 \right)$$

Where G_p is the paint gain, DN_{mean} is the time averaged mean counts, and DN is the counts in a particular frame. Using a Taylor series approximation about $DN=DN_{mean}$, the variance of ΔP is found as below:

$$Var(\Delta P) = \frac{G_p^2}{DN_{mean}^2} Var(DN)$$

The variance of the measured counts $Var(DN)$ is the sum of the shot noise, read noise, and true pressure signals. The variance of the shot noise and read noise portion is found as below.

$$Var(\Delta P_{noise}) = \frac{G_p^2}{DN_{mean}^2} (G_c DN_{mean} + Var(DN_{read})) \quad (2)$$

If the paint calibration, camera noise characteristics, and the time mean counts are known, Eq. (2) can be used to estimate the contribution of the noise to the measured fluctuating pressure signal. We can call this quantity the ‘noise floor’. This would be the fluctuating pressure measured in a wind-off condition when there is no true signal.

The relation above applies for a single pixel. Generally, many pixels are averaged together in these measurements to reduce the noise level. The variance in ΔP_{noise} will then decrease as $1/N$, where N is the number of pixels averaged together. Figure 6 below is a plot of this relation for a particular reference temperature and pressure, showing how the noise floor expressed in sound pressure level (SPL) changes with DN_{mean} . The noise reducing effect of spatially averaging together adjacent pixels is also shown. In practice, using a very large spatial average does not continue decreasing noise as $1/N$ – the variance is eventually dominated by PRNU between pixels rather than random noise. In addition, the decorrelation of the true pressure signal should be considered for large averaging areas, especially if that area is significantly larger than a pressure transducer being used for comparison.

The form of the equation also provides some insight on what can be done to reduce the noise floor. The options are to improve the camera noise characteristics (reduce read noise and/or reduce camera gain), increase the lighting level (increase DN_{mean}), or use a less sensitive paint (reduce G_p). However, the relationship between the intensity of paint emission (which affects DN_{mean}) and the paint gain will need to be modeled in order to determine if there is a net benefit to using a less sensitive paint. Also, the dynamic range and bit depth of the camera set a lower limit on paint gain – too small of a paint response will result in no change in measured counts.

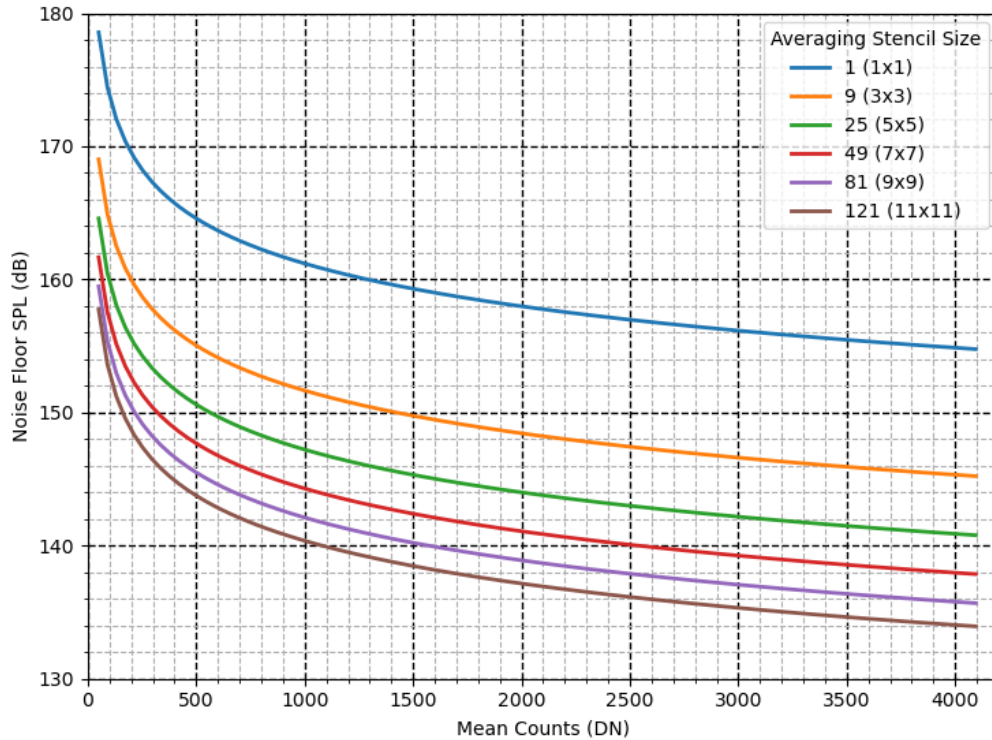


Figure 6: Variation of noise floor with mean counts and number of pixels averaged. Evaluated using a representative paint calibration, at a reference condition of 68°F and 2116 psf.

In Eq. (2) the paint gain G_p is a function of temperature and pressure. When expressed in sound pressure level SPL (which uses the root-mean-square of ΔP instead of the variance), the noise floor is linear in the quantity G_p . Thus, on the logarithmic scale used in Figure 6, the effect of changing temperature and pressure is to change the gain, which in turn shifts the curve up or down by the quantity $20 \log \left(\frac{G_p}{G_{p,ref}} \right)$, where $G_{p,ref}$ is the gain at some reference condition. Here, the reference condition is taken to be 68°F and 2116 psf. It is possible to create a contour map that uses this fact to scale the noise floor to different temperature and pressure conditions. Such a map is shown below in Figure 7.

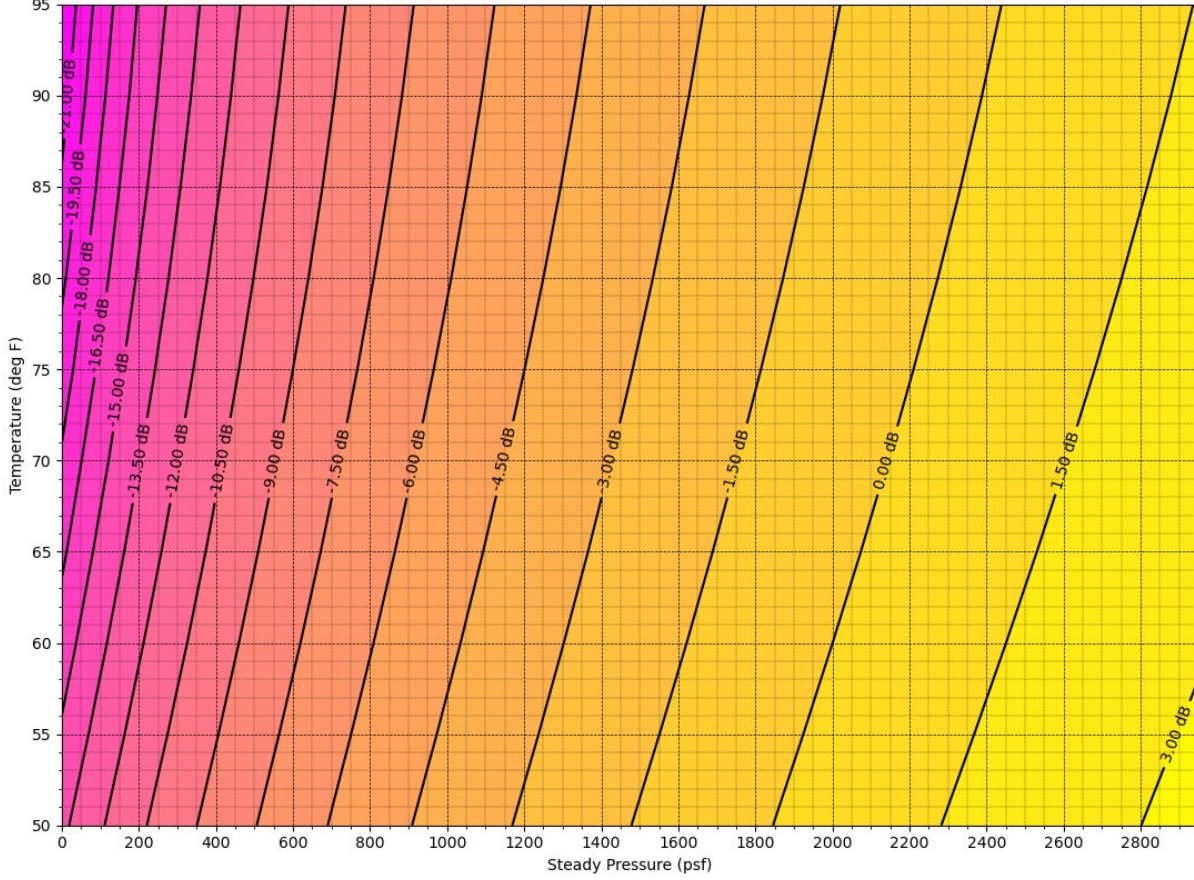


Figure 7: Noise floor correction map.

The two plots Figure 6 and Figure 7 can be used to estimate noise floor across different conditions. For example, while using a using a 3x3 area average, a time mean grey level of 2000 counts is observed at a model temperature of 55°F and steady pressure of 750 psf. Figure 6 shows that the noise floor at the reference condition at 2000 counts is 148.5 dB. Using Figure 7, we can see that at 55°F / 750 psf the noise floor is reduced by 6 dB relative to the reference condition. Thus, the noise floor is estimated as 142.5 dB. These maps are an easy, intuitive way to understand how the noise floor changes with different conditions and are helpful in test planning and evaluating data quality. If these formulas are integrated into a data acquisition system, the noise floor for newly-acquired data can be quickly estimated without going through the entire uPSP data reduction pipeline. The process can also be used in reverse to estimate what mean grey level is required in order to achieve a particular noise floor. Of course, these calculations can also be automated to produce noise estimates without manually using these plots.

A similar analysis can be used to estimate errors in steady pressures obtained by the lifetime method. The paint calibration relates the lifetime ratio R_L (defined as the ratio DN_{gate2}/DN_{gate1}) to a steady pressure P at a particular temperature T – that is, $P(R_L, T)$. The analysis begins again with the variance of a linear Taylor series approximation of the paint calibration.

$$Var(P) = \left(\frac{\partial P}{\partial R_L} \right)^2 Var(R_L)$$

The partial derivative term is derived directly from the paint calibration. The variance of the lifetime ratio can be found using a bivariate Taylor series approximation about DN_{gate2} and DN_{gate1} .

$$Var(R_L) = Var\left(\frac{DN_{gate2}}{DN_{gate1}}\right) \approx \left(\frac{DN_{gate2}}{DN_{gate1}}\right)^2 \left[\frac{Var(DN_{gate2})}{DN_{gate2}^2} + \frac{Var(DN_{gate1})}{DN_{gate1}^2} - 2 \frac{Cov(DN_{gate2}, DN_{gate1})}{DN_{gate2} DN_{gate1}} \right]$$

Using the definition of R_L , Eq. (2), and the statistical independence of the Gate 1 and Gate 2 measurements, this reduces to the following:

$$Var(R_L) = \frac{R_L^2}{DN_{gate1}} \left[G_c \left(1 + \frac{1}{R_L}\right) + \frac{Var(DN_{read})}{DN_{gate1}} \left(1 + \frac{1}{R_L}\right) \right] \quad (3)$$

Combined with a paint calibration, Eq. (3) can be used to estimate the uncertainty due to read and shot noise in a steady pressure measurement. However, in our application we generally have tens of thousands of frames available over which to perform time averages. The read noise of our high-speed cameras is high, but the extremely large number of samples allows us to average out most of the random noise. Instead, the error in our steady pressure measurements is dominated by bias errors such as PRNU or inaccuracy in paint calibration.

III. Results

In the Launch Vehicle Demo Test (LVDT), each day began and ended with a pumpdown paint calibration, where the pressure in the tunnel circuit was reduced and uPSP data points taken while wind-off (Mach = 0). The uPSP data points were taken in both intensity and lifetime mode. Figure 8 shows a comparison between experimental pumpdown data (indicated by markers) and the paint model fit (indicated by solid lines). The fit was performed on a sample LVDT data point, on a 24 pixel by 24 pixel area near a pressure transducer. Red color indicates lifetime mode, where the quantity of interest is lifetime ratio (Gate 2 / Gate 1). Blue indicates intensity mode. The model was fit using only the lifetime mode data, which consists of five Gate 2 images and five Gate 1 images. This provides ten observations to determine the five fit parameters I_{0A} , I_{0B} , τ_{0A} , τ_{0B} , and k_{qA} . The intensity mode data was not used in generating the fit. It was observed that the measured counts in intensity mode is consistently about 90% of the model's predicted intensity mode counts. The exact percentage is notated next to the markers on the figure. This pattern holds true across the entire model. This behavior is attributed to a difference in average lamp power output when run at the intensity mode's 100% duty cycle, as opposed to the lifetime mode's 50% duty cycle.

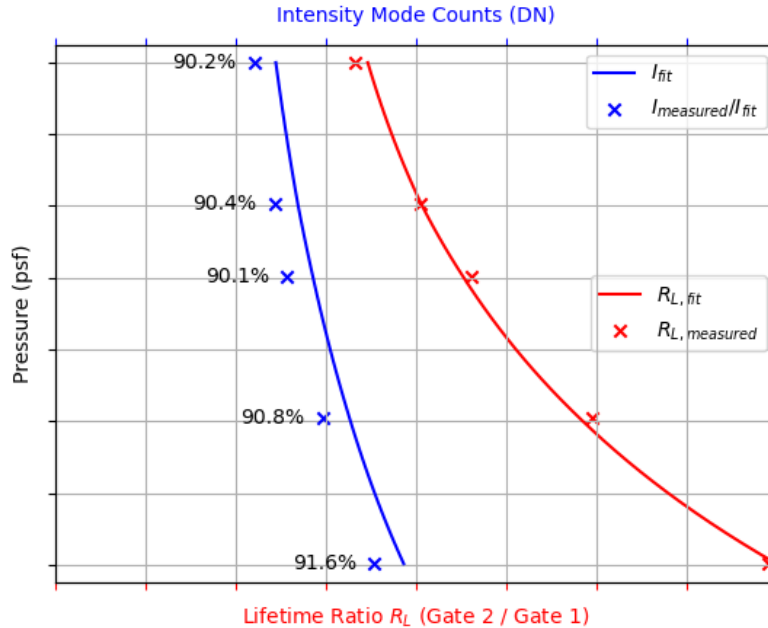


Figure 8: Paint calibration obtained using pumpdown data.

Figure 9 below shows the paint calibration (both lifetime mode and intensity mode) derived from the pumpdown data shown in Figure 8. During the pumpdown, only a small temperature range of 66°F to 71°F was covered (as measured by thermocouples embedded in the model). The model fits that limited temperature range but also provides a smooth extrapolation over a much wider temperature range. The pumpdown paint calibration obtained here is actually appreciably different from the laboratory coupon paint calibration shown in Figure 4. That coupon was painted at the same time as the model, using the same batch of paint and the same equipment as the wind tunnel model. This highlights the importance of performing in-situ pumpdown paint calibrations. In addition, the paint calibration also differs appreciably between different locations on the model, as can be inferred from the spatial variation in fit parameters shown previously in Figure 5.

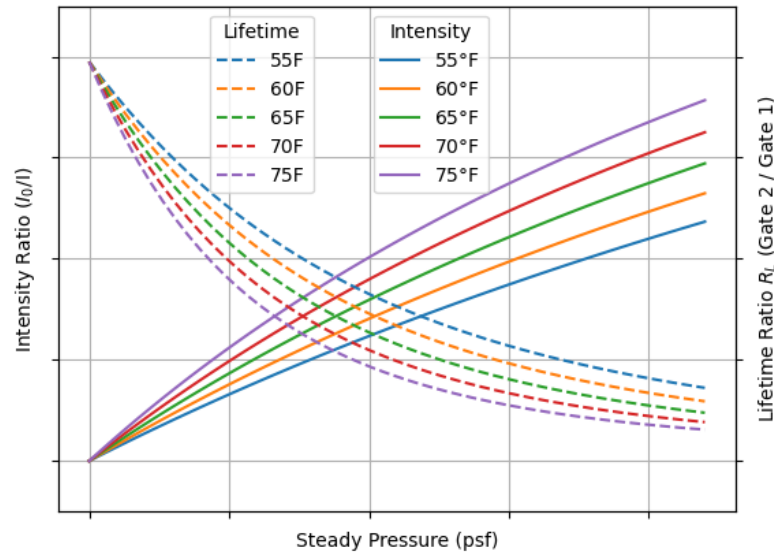


Figure 9: Paint calibration obtained from pumpdown data. Dotted lines show lifetime ratio response, solid lines show intensity ratio response.

From the above paint calibration, the unsteady paint gain can be obtained as the derivative of intensity ratio with respect to pressure, multiplied by the intensity ratio. The resulting gain calibration is shown below. The nonlinearity with respect to pressure is an immediately noticeable feature. According to this fit, the paint gain becomes less sensitive to temperature at higher pressures, and the behavior becomes non-monotonic at the highest pressures (gain first decreases with increasing temperature, then increases as temperature is raised further). This may be an artifact of fitting to a limited temperature range.

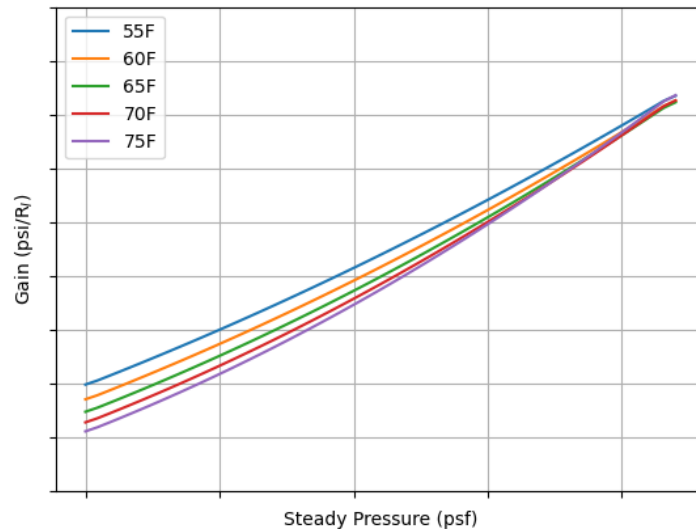


Figure 10: Unsteady paint gain calibration obtained from paint calibration.

The application of this pumpdown paint calibration to sample wind-on data is shown below in Figure 11. The Mach number increases with increasing sequence ID along the x-axis. The Mach range covered is from 0.5 to 1.4 in increments of 0.1. A 24x24 pixel area was used to obtain uPSP results. This area was located near a Kulite absolute pressure transducer. In the figure, the color orange indicates data taken from the Kulite and the color blue indicates values obtained from uPSP. The solid blue line is steady pressure measurements (psf) taken using the lifetime method. The dotted blue line is sound pressure levels obtained using the intensity method (dB).

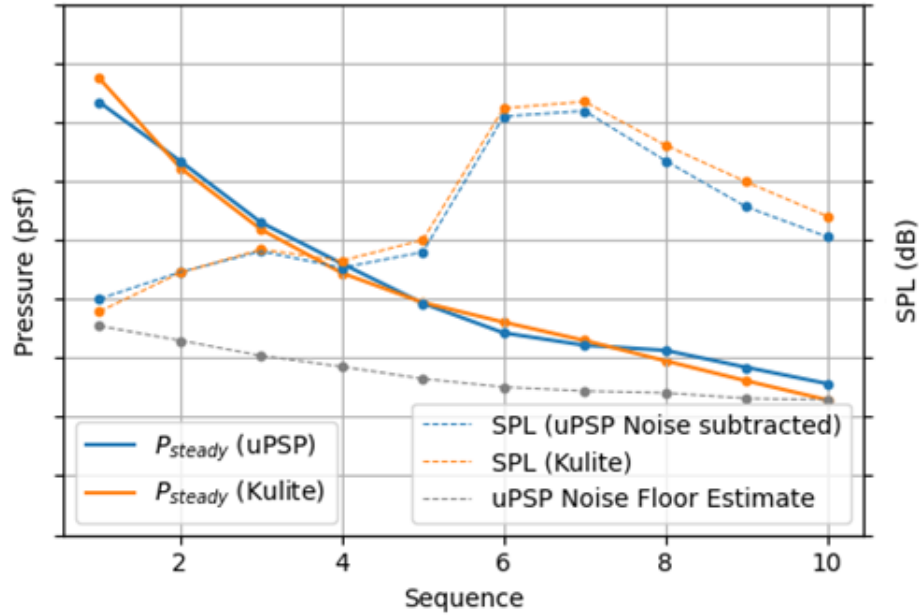


Figure 11: Comparison of uPSP steady and unsteady pressure results to absolute pressure transducer (Kulite)

Comparing to pressure transducers, the steady pressures measured by uPSP demonstrate acceptable accuracy (within ~100 psf) across the sequence IDs. In uPSP, the steady pressure is not a data product in itself. It is only used to determine the unsteady paint gain, and that gain is not strongly sensitive to steady pressure. Steady pressure errors of up to ~100 psf have only a minor effect relative to other sources of error, particularly compared to errors in paint temperature. In this work, a simple recovery factor method based on the difference between total temperature and freestream static temperature was used to estimate temperature. With this simple method, the quality of Kulite to uPSP comparison will depend greatly on how well this assumption works at the selected location on the model.

The sound pressure levels obtained by uPSP and the levels measured by the Kulite are shown as dashed lines on the figure. The blue uPSP line has had the noise level subtracted from the raw uPSP measurement. The largest deviation between Kulite and uPSP is approximately 2.2 dB. In previous work, uPSP results were ‘anchored to Kulites’, meaning that an empirical correction factor was applied to the paint gain in order to make the uPSP SPL match the Kulite SPL. The use of an in-situ paint calibration significantly reduces the size of the correction factor that must be applied.

The uPSP noise floor estimate, obtained by the method described in the previous sections, is shown as the grey dashed line. It is highest at low Mach number and high pressure (where the paint is dimmest) and reduces as the Mach number increases (and the paint luminesces more brightly). Note that in this example the noise floor is always below the measured uPSP SPL, although only marginally so at the lowest Mach number. At other Mach numbers the noise floor is comfortably below the measured signal level. For higher pressure locations or locations that are dimly lit, the uPSP signal may be at roughly the noise floor level and little actual signal is discernable.

Figure 12 below shows the power spectral densities of the raw uPSP signal, the noise floor subtracted uPSP signal, and Kulite signal at the first (lowest Mach number) wind-on data point.

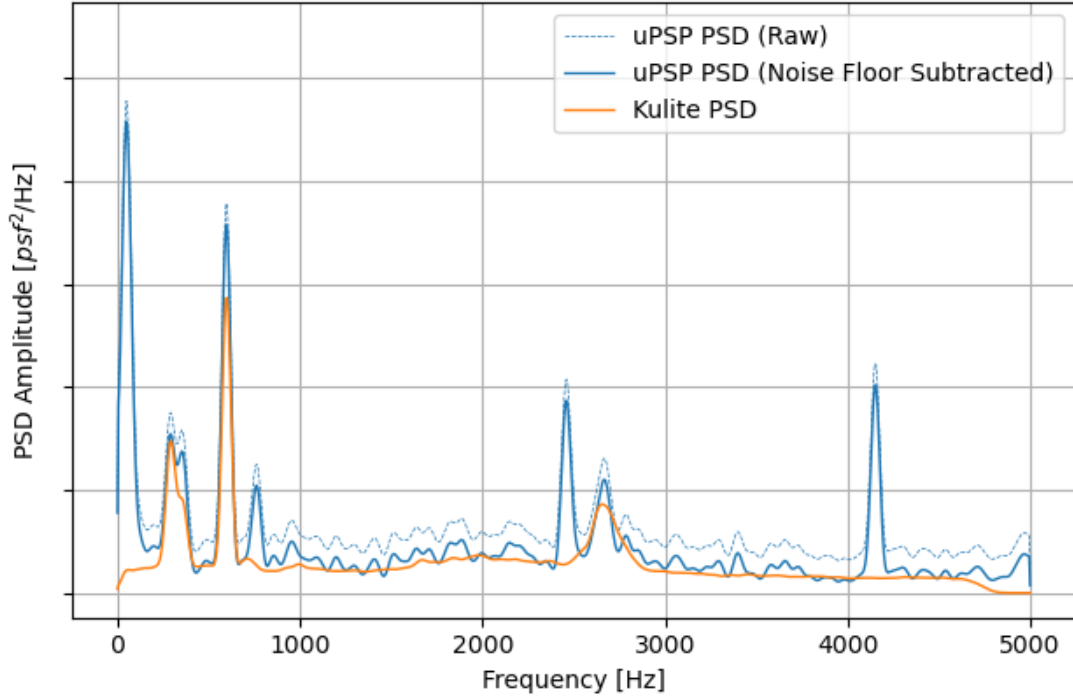


Figure 12: Comparison of power spectral density between pressure transducer (Kulite) and uPSP.

Here, the overall agreement between the Kulite and uPSP signal is good, apart from the spurious uPSP peaks associated with time-varying camera pattern noise at 750 Hz, 2450 Hz, and 4150 Hz. The uPSP peak at very low frequency (~ 50 Hz) is likely due to model motion and can also be ignored. When the noise floor is subtracted via the methods described in the preceding sections, the Kulite and the uPSP show closer agreement. At higher Mach numbers, the noise floor becomes so small relative to the signal level that the noise floor subtraction process does not significantly affect the raw uPSP PSD.

IV. Conclusion

An analytical method for providing noise estimates for both the fluctuating component of pressure (obtained through the intensity method) and steady component of pressure (obtained through the lifetime method) is presented. The process begins with obtaining a paint calibration and noise characteristics for the cameras. A new paint model for pumpdown paint calibrations is presented. The propagation of camera shot noise and read noise through the PSP working equations is modeled. The effect of bias errors introduced by errors in paint calibration and camera photo response non-uniformity are also discussed. The results of these noise modeling steps is compared to wind tunnel data. The error estimation method developed is useful in understanding the behavior of the noise floor with varying illumination level and test conditions (temperature and pressure). It is also a tool for providing estimates of expected data quality before a uPSP test is conducted, and can be used to provide data quality estimates during data acquisition as a diagnostic tool, before the full processing can be performed.

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