

Data Normalization Schemes for Assessing Mixture Stratification from PLIF Data

R. E. Herold and J. B. Ghandhi

Engine Research Center; University of Wisconsin – Madison

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ABSTRACT

Planar laser-induced fluorescence (PLIF) has become a useful diagnostic for the quantification of in-cylinder flowfield conditions, and in many applications determining the homogeneity of the in-cylinder flowfield is of primary importance. In some cases, noise associated with this imaging technique (i.e., camera noise, shot-to-shot laser energy variation, and laser sheet profile variations) can dominate the flowfield inhomogeneities, leading to biased mixture stratification statistics. Presented herein are three data normalization schemes (global-, image-, and ray-mean) that can be used to correct for these noise sources when assessing mixture stratification from PLIF data. The normalization schemes are applied to in-cylinder PLIF data obtained over a wide range of inhomogeneity levels, and the conditions over which the use of each normalization scheme is appropriate are discussed.

INTRODUCTION

Charge mixture stratification plays a significant role in a wide variety of engine combustion applications. In some cases understanding large-scale stratification, which in the present context is considered to be a gradient that spans several integral length scales, is important. For example, in lean direct-injection gasoline engines a necessary condition is that an ignitable concentration of fuel vapor be present at the desired ignition timing over a wide range of operating conditions. Optical measurements of the fuel vapor concentration can be performed using planar laser-induced fluorescence (PLIF); by ensembling the results over many cycles an understanding of the large-scale fuel distribution can be achieved with good accuracy. To first order, this allows an assessment of whether there are parts of the operating range where ignition limitations may exist. The averaging, which is necessary to reduce the effects of cyclic variability, helps reduce noise in the measurements, and good accuracy can be achieved. The cyclic variations are also important for ignitability, and by defining a local region near the spark and (ideally) integrating over a time commensurate with the

spark discharge [1,2] the effects of local mixture variations can also be assessed.

Small-scale inhomogeneities in flows that do not exhibit large-scale stratification can also be important. The mixing between the intake charge and the internal residual gas is nearing completion at top dead center and, unless special measures are undertaken, the fresh mixture will be nearly homogeneously dispersed within the cylinder. There are, however, small-scale variations in the composition (and thus temperature); these variations can affect the combustion event. Local regions with a higher than average level of residual gas in a spark-ignition engine may lead to an increased flame development time. In homogeneous charge compression ignition (HCCI) engines, these small-scale inhomogeneities have been shown to directly affect combustion. Chemiluminescence [3,4] and PLIF imaging of fuel [5] and combustion intermediates, such as formaldehyde [6,7], show that ignition occurs simultaneously in multiple locations within the chamber in spite of the supposedly homogeneous field. The staggering of the ignition timing of the mixture based on the local conditions has been shown to moderate the pressure rise rate, and it has been suggested that augmenting this effect could possibly extend the high-load limit of HCCI combustion [8].

The level of small-scale inhomogeneity is difficult to measure optically with high accuracy. Most optical imaging techniques are limited by signal strength, *i.e.* shot noise, constraints. High quality image data typically have shot-noise limited signal-to-noise ratios of $\sim 20:1$. This implies that any given pixel can have a value, with 95% confidence, that is $\pm 10\%$ of the mean value. However, in many instances this level of precision is not sufficient – Sjöberg *et al.* [8] indicate that introducing a $\pm 5\%$ temperature stratification ($380\text{ K} \pm 10\text{ K}$, represented by 4 independent zones) was sufficient to match the measured pressure rise rate from HCCI combustion using a multi-zone chemical kinetic model. Spatial averaging (filtering) can help to reduce this noise floor, but it adds a bias (*i.e.*, it eliminates true fluctuations) if the filter width is larger than the smallest

turbulent length scales in the flow, which in engines can approach 50 μm [9]. There are other practical measurement issues that also impact the ability to identify small-scale inhomogeneity associated with: sampling biases due to the limited field of view, the laser operation (variations in the pulse-to-pulse energy and spatial beam profile), beam steering within the cylinder, and noise sources within the camera, for example. These problems are depicted graphically in Figure 1.

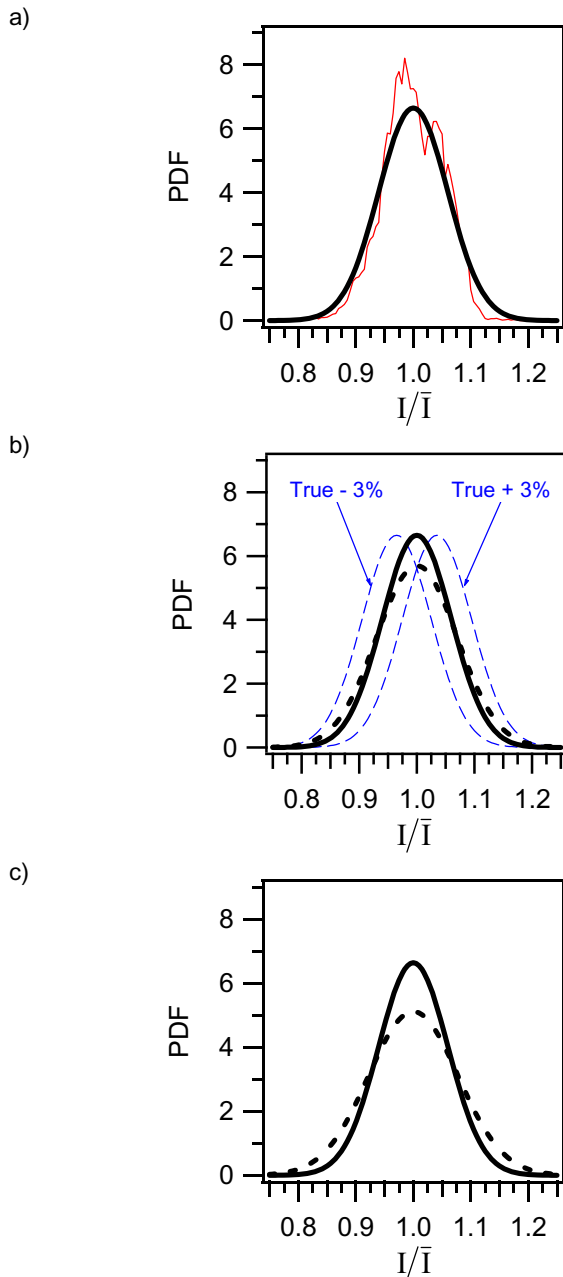


Figure 1. Changes in the estimated 'true' distribution, shown in the solid bold line, from (a) under sampling, (b) systematic bias associated with laser energy variations, (c) measurement noise. In (b) and (c) the estimated measured PDF is shown in the dashed bold line.

Figure 1a shows the probability density function (PDF) of pixel intensity from an individual PLIF realization taken in our laboratory, shown in the narrow line, along with an estimated 'true' distribution, which for the sake of discussion here is shown using a Gaussian function and the bold line. The PDFs are normalized such that $\int p(x)dx = 1$, and their width can be characterized by the

second moment, σ , which was 0.051 and 0.06, respectively, for the measured and true distributions shown. It is clear that the individual realization is close to the presumed true value, but there are differences between the two – the PDF is not fully converged. This represents a sampling bias, and it arises because only a limited part of the flowfield can be interrogated by a single measurement, which underscores the need to ensemble data from several different realizations to improve the convergence. But this process also introduces other biases into the measurements. Figure 1b shows the simulated effect of shot-to-shot laser energy variations. The two dashed narrow lines represent the true profile with 3% higher and 3% lower mean values, which would result from the typical RMS energy variability for a pulsed solid-state laser in the ultraviolet, and the dashed bold line is the estimated measured PDF. It is clear that the measured PDF is broader than the true distribution. A laser energy correction can be performed, but requires part-per-thousand accuracy, which can in principle be achieved, but with considerable effort. The effects of random noise that arises from noise in the detection system, uncorrectable laser profile variations due to beam steering and other effects will also act to widen the measured distribution. These effects are depicted in Fig. 1c, where a 5% noise (corresponding to a 20:1 signal-to-noise ratio) was added to the true distribution.

The objective of this paper is to investigate the measurement issues that limit the acquisition of image data that will allow an assessment of the small-scale mixture inhomogeneity. This will include post-processing operations that minimize the biases discussed above, allowing the small-scale mixture homogeneity to be assessed. Conditions where these operations are and are not appropriate will be discussed quantitatively.

STANDARD IMAGE PROCESSING

For experiments detailing the in-cylinder charge mixture stratification, data, flatfield, and background images are typically acquired at each operating condition. Data images are acquired when the stratified conditions are being produced (e.g. during fired operation or when employing direct fuel injection), flatfield images are acquired with homogeneous fueling and motored engine operation, and background images are acquired with no fueling and standard engine operation. A statistically significant number (typically 100) of each image type are acquired. Data images are corrected for the influence of

background signal and the non-uniform spatial profile of the laser using

$$I_{r,c,n}^{corr} = \frac{I_{r,c,n} - \langle I_{r,c,n}^b \rangle_{r,c}}{\langle I_{r,c,n}^f - \langle I_{r,c,n}^b \rangle_{r,c} \rangle_{r,c}} S \quad (1)$$

where I is the pixel intensity, the superscripts $corr$, b , and f refer to the corrected, background, and flatfield images, respectively; the subscript r and c refer to the pixel location, where r is parallel to and c is perpendicular to the laser-propagation direction, the subscript n refers to the image number within an image set; the $\langle \rangle$ brackets refer to ensemble averaging over the full image set (see Appendix for mathematical formulation); and S is a representative value that scales the resulting image intensities back to units of camera counts. In our laboratory, S is chosen to be the maximum pixel intensity in the ensemble average background corrected flatfield image, although any representative value could be used.

DATA NORMALIZATION SCHEMES

To quantify the levels of unmixedness captured in the PLIF images, probability density functions (PDFs) of the image sets are compiled along with the second moments of the PDF distribution, σ . Prior to the PDF calculations, three data normalization schemes can be employed: global-, image-, and ray-mean normalization.

Global-mean normalization, where the pixel intensities are normalized by the average pixel intensity of the entire data set, can be described as

$$I_{r,c,n}^{gl} = \frac{I_{r,c,n}^{corr}}{\langle \bar{I}_n \rangle} \quad (2)$$

where the superscript gl indicates global-mean normalization, and the overbar indicates spatial averaging over the entire image (see Appendix). Image-mean normalization is performed by normalizing the pixel intensity by the spatial mean pixel intensity of its particular image and can be described as

$$I_{r,c,n}^{im} = \frac{I_{r,c,n}^{corr}}{\bar{I}_n} \quad (3)$$

where the superscript im indicates image-mean normalization. With ray-mean normalization, each pixel intensity value is normalized by the mean pixel value along the laser propagation direction and can be described as

$$I_{r,c,n}^{ray} = \frac{I_{r,c,n}^{corr}}{\tilde{I}_{c,n}} \quad (4)$$

where the superscript ray indicates ray-mean normalization, and the tilde indicates spatial averaging over the ray direction only (see Appendix). To observe the effects of these normalization schemes and to determine their applicability, the normalizations will be applied to PLIF data acquired in our laboratory. To start, the effects of normalization will be observed for a single PLIF data set, and then a more general description of the effects will be presented by applying the normalizations to PLIF data sets acquired in different optically accessible engines, with various imaging systems, and with various levels of mixture stratification.

HOW NORMALIZATION AFFECTS PDF

The effect of the different normalization schemes will be demonstrated using data acquired in experiments detailing residual gas mixing in engines [10]. The data set of interest was acquired at 45 °bTDC under a modest engine load condition and 600 rpm. At this engine condition, a low amount of residual is achieved, and as a result a low amount of unmixedness in the in-cylinder charge is expected. Data, flatfield, and background images were acquired and the standard image correction was applied. Additionally, a 3 x 3 median filter was applied after the image correction. A median filter has been shown to reduce noise while preserving gradients [11], but can only be applied if the noise is spatially uncorrelated. The applicability of the median filter was addressed by Bright [10] and will be discussed below.

The PDFs of the corrected pixel intensities, prior to any normalization, are shown in Fig. 2a. Direct comparison between the data (bold line) and flatfield (narrow line) conditions is difficult when using PDFs of corrected pixel intensities. The PDFs are offset along the abscissa, i.e. there were different signal levels, and the PDF normalization then skews the heights. To make a direct comparison between the data and flatfield PDFs, global-mean normalization can be used (Fig. 2b). By normalizing with the ensemble-average spatial-mean pixel intensity, the PDFs can be used for direct visual comparison.

The global-mean normalized PDFs shown in Fig. 2b reveal little difference between the data and flatfield conditions, which would imply for the engine condition under consideration there is no mixture stratification being produced. A sample of 25 corrected images (shown with an expanded greyscale to allow small deviations about a large pedestal to be observed) for the data (Fig. 3a) and flatfield (Fig. 3b) conditions, however, qualitatively do not support this conclusion. The corrected data images appear to show some

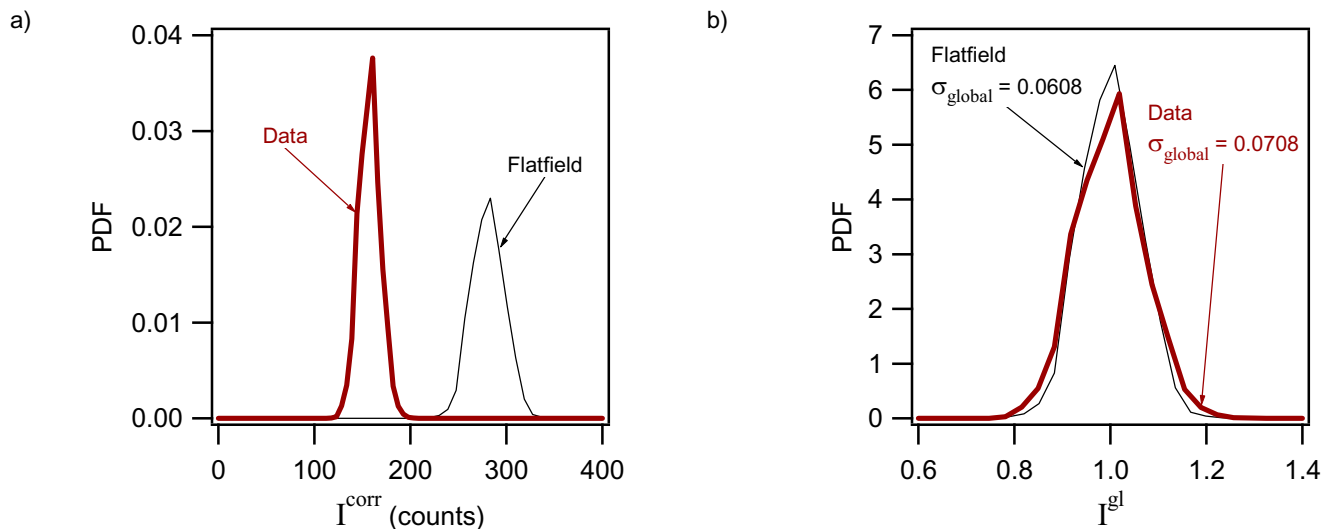


Figure 2. PDF distributions (a) corrected and (b) global-mean normalized pixel intensities for data (bold) and flatfield (narrow) conditions.

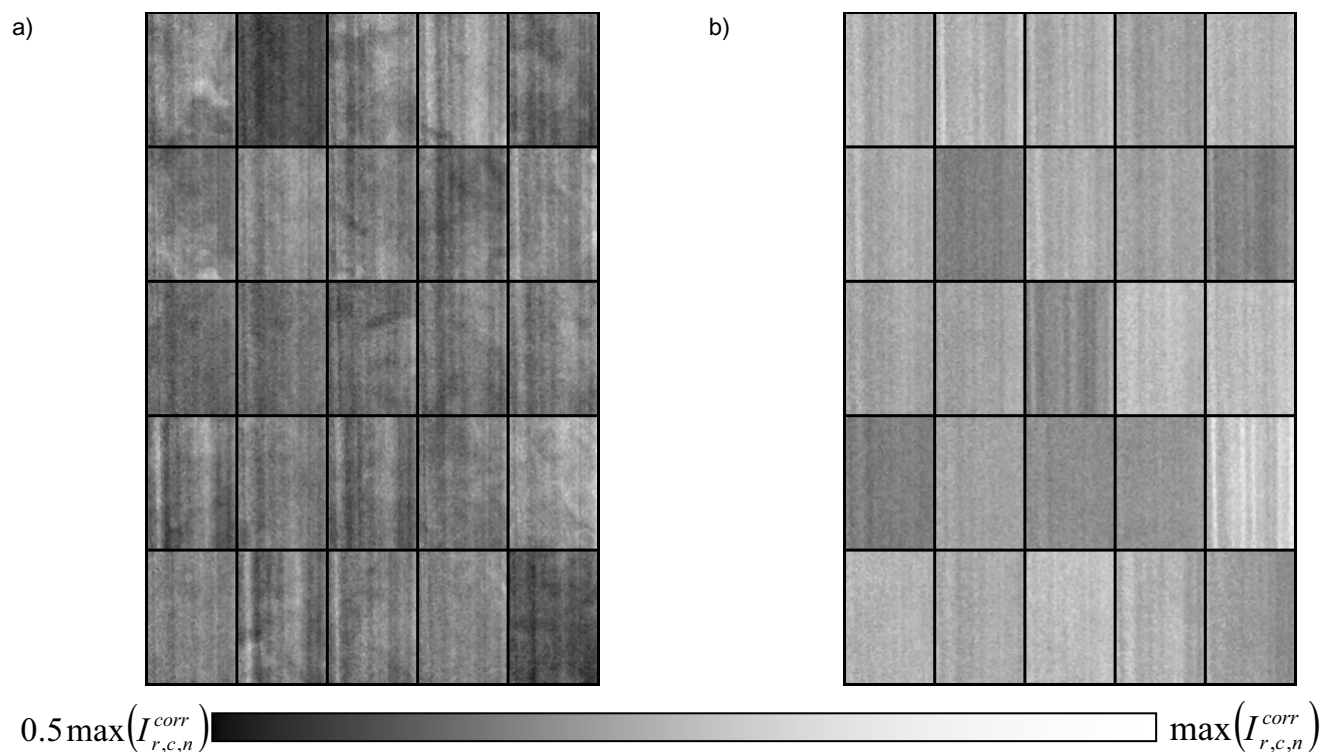


Figure 3. Twenty-five sample corrected images for (a) data and (b) flatfield conditions. The sample images are for the PDFs shown in Fig. 2.

unmixedness that is absent in the corrected flatfield images. The global-mean normalized PDFs are unable to resolve the differences in the mixture stratification between the data and flatfield conditions. The corrected images, as shown in Fig. 3 with all images displayed on the same grey scale, indicate why this is the case. Significant shot-to-shot variations are evident in the images, both in the total amount of fluorescence (changes in the mean image intensity) and in the laser sheet profile (changes in the vertical striations within each image). The flatfield PDF has $\sigma = 0.0608$, giving a 16:1 signal-to-noise ratio (SNR), but using this data processing scheme the small level of stratification is

indistinguishable from noise, which motivates the use of the image- and ray-mean normalization schemes.

Unlike the global-mean normalized PDFs, the image-mean normalized PDFs (Fig. 4) for the data (bold line) and flatfield (narrow line) images are significantly different. The data PDF has a wider distribution than the flatfield PDF, indicating more stratification in the data image set and confirming the qualitative observation made from the corrected images (Fig. 3). Both PDFs in Fig. 4 are narrower than their counterparts in Fig. 2b, which is an expected effect of the image-mean normalization. The global-mean PDF is essentially a compilation of the image-mean PDFs.