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Deconvolution uncertainty for power sensors at the National Ignition Facility

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ABSTRACT

We used a Monte Carlo method to generate error bars for deconvolved measurements from diagnostics on the National Ignition Facility (NIF). Through a process of masking and normalization of the diagnostic system's known Impulse Response Function (IRF), we were able to diminish the deconvolved measurement error for all points of the waveform by a factor of > 2. This technique is generally applicable to deconvolutions with measured IRFs.

Key words: Laser diagnostics, deconvolution, error estimation

1. INTRODUCTION

The National Ignition Facility (NIF) has over 100 power sensors on its beamlines to measure pulse shape via a photodiode and digital oscilloscope. A deconvolution of the acquired data is performed using the system's measured Impulse Response Function (IRF). Since both the measured pulse and measured IRF are susceptible to measurement noise, the noise from both components will propagate to the deconvolved result. Signal pre-processing of both deconvolution inputs can minimize the contributions of measurement noise to the deconvolution, though some form of deconvolution error propagation is necessary to inform and verify the efficacy of the pre-processing techniques employed.

Some attempts have been made to analytically propagate error in deconvolution[1] and Fourier transforms[2], though Monte Carlo error propagation is the most general solution[3]. The Monte Carlo approach correctly propagates any noise reduction due to pre-processing of the deconvolution inputs without extended analytical derivation. In the work here, we use a Monte Carlo simulation to propagate our measurement noise through the deconvolution algorithm, and use this to inform the choice of signal pre-processing techniques employed to minimize the propagated error. The resulting error propagation is further used to affix error bars on deconvolved results.

2. METHODS

The simulation was performed in MATLAB (Figure 1). An initial signal input and IRF were estimated from acquired measurements. The data and IRF were convolved, and then noised to match the system's noise spectrum. The IRF was then independently noised to match this same noise spectrum. The noisy convolved data and noisy IRF were the two inputs to the deconvolution. After generating these, a four stage algorithm to perform the deconvolution and error analysis was used: mask the IRF, normalize the IRF, apply a filtered deconvolution, and generate error statistics via a Monte Carlo simulation.

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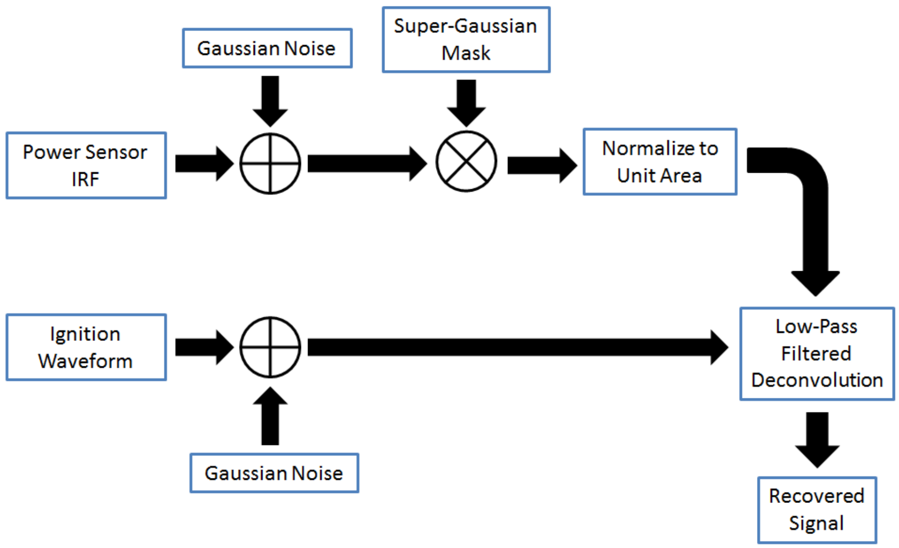

Figure 1. Block diagram of deconvolution process. The process was repeated 10000 times to perform the Monte Carlo simulation in generating the error statistics.

The IRF has very narrow duration in time compared to its record length – only 4-5 ns of the 50 ns record account for the IRF, the rest being noise (Figure 2). To process the IRF and remove this extraneous noise, the IRF was masked, with start and stop boundary points identified where signal magnitude rises above and falls below the noise floor for ≥ 5 samples, respectively. A 5th order Super-Gaussian mask was used. After masking, we normalize the IRF to have the same area as the original noised IRF. After processing the IRF, a 5th order Super-Gaussian low-pass filtered Fourier deconvolution is performed.

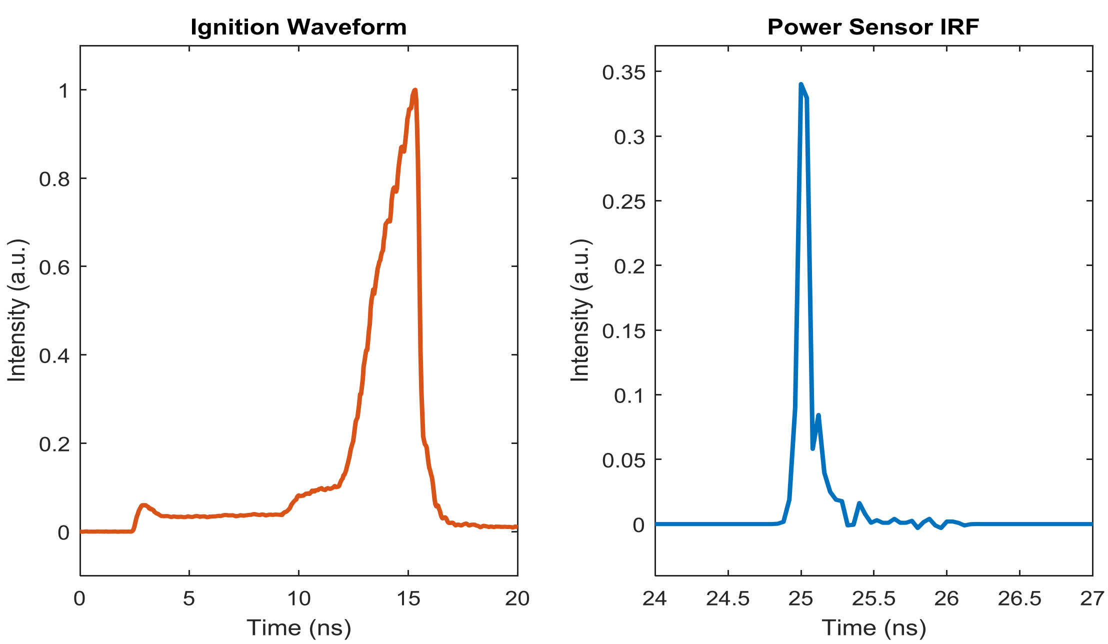

Figure 2. Ignition Waveform and Power Sensor IRF. The IRF's duration, including the settling time, is ~10x shorter than the waveform's.

To propagate the error of this deconvolution, a Monte Carlo simulation was used. The above process was repeated with the same noise spectrum across a large number of trials, and the standard deviation of the deconvolved results at each point in time is the propagated error. 10000 trials was found to be adequate for obtaining consistent estimates of the propagated error.

3. RESULTS AND DISCUSSION

Figure 3 shows the propagated error of the deconvolved results. The fill lines have a height of three times the standard deviation at that point, so that they act as a 99.7% confidence limit on the margin of error at that point. The new methods of masking and normalization show a reduction in error by a factor of > 2 over the previous methods (Figure 3). In addition to the reduction of error of the deconvolution, the error margins for acquired data can now be predicted using this technique.

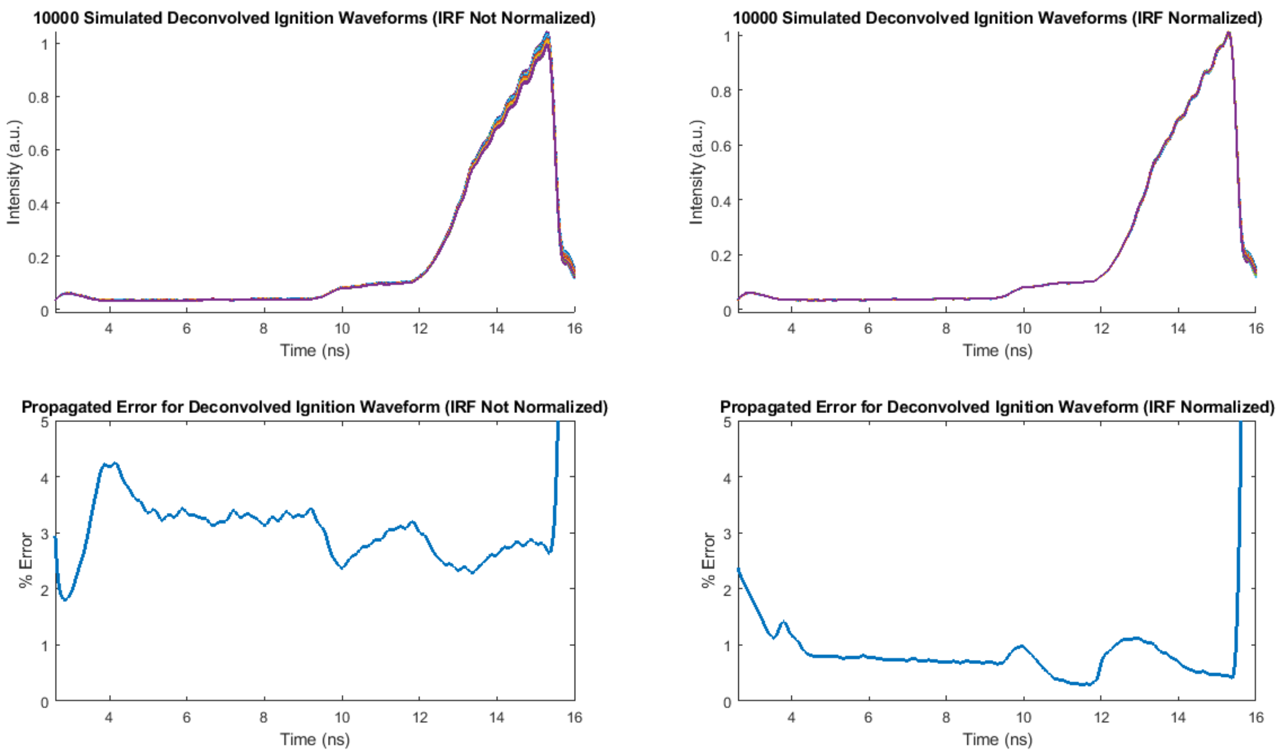

Figure 3. Compared to not normalizing the noisy IRF (left), normalizing the IRF (right) resulted in deconvolutions with substantially decreased amplitude error. In addition, error margins for acquired data can now be predicted with this technique.

The two processing techniques used to achieve this reduction in error were masking and normalization of the IRF. Masking the IRF improved its signal-to-noise ratio by removing noisy regions without affecting the true signal. A conservative approach to masking was taken to err on the side of letting in extra noise rather than masking out signal. Noising perturbs the integrated area of the ignition waveform; renormalizing removes this perturbation, and reduces the noise of the deconvolved waveform. The techniques of masking and normalization can be applied to any IRF by identifying where the signal drops below the noise floor to achieve similar improvements. The method of generating error bars using a Monte Carlo simulation is more broadly applicable to any deconvolution involving a measured IRF and data.

These same techniques were also applied to the ignition waveform with limited results. Compared to the IRF waveform, which had ~50 samples that remained unmasked, the ignition waveform had ~1000 samples that remained unmasked. Due to the large number of samples of the ignition waveform, the perturbation of the integrated area by noise is significantly less than for the IRF.

The Monte Carlo simulation successfully propagated the measurement noise through the deconvolution algorithm without extended analytical derivation. However, the Monte Carlo procedure is very computationally intensive, and would require additional effort to make it compatible with real-time applications. Since the iterations of the Monte Carlo simulation are independent, and its runtime is dominated by FFT operations, the procedure is highly computationally and GPU parallelizable.

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