Pulse Pile-up Deconvolution Methods via Machine Learning

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Abstract

Conventional approaches to deconvoluting piled-up waveforms produced by scintillator gamma detectors use techniques such as FFT filtering to approximate the true arrival times and amplitudes of the individual pulses within the waveform. Although these approaches are effective, a method with an improved deconvolution rate and accuracy is desirable. We have, therefore, developed a variety of deconvolution techniques using machine learning—including a method using unsupervised learning, which requires no conventional techniques to be performed on the data beforehand in order to obtain a ground truth

The data for Approach 1 and 2 were collected via a positron beam—the piled-up pulses are therefore due to the delayed annihilation of re-emitted positronium (Ps).

Approach 1: Wiener Deconvolution-based

Wiener deconvolution is a conventional technique that uses an FFT high-pass filter with the following Fourier space formulation:

$$H(\omega) = \frac{R(\omega)^*}{|R(\omega)|^2 + |R(\omega_c)|^2}$$

Fig. 1 is a comparison of the raw and filtered waveforms from [1]; Fig. 2 provides a correlation of the filtered pulse peak heights and estimated energy deposition from integrating the raw waveforms [1].

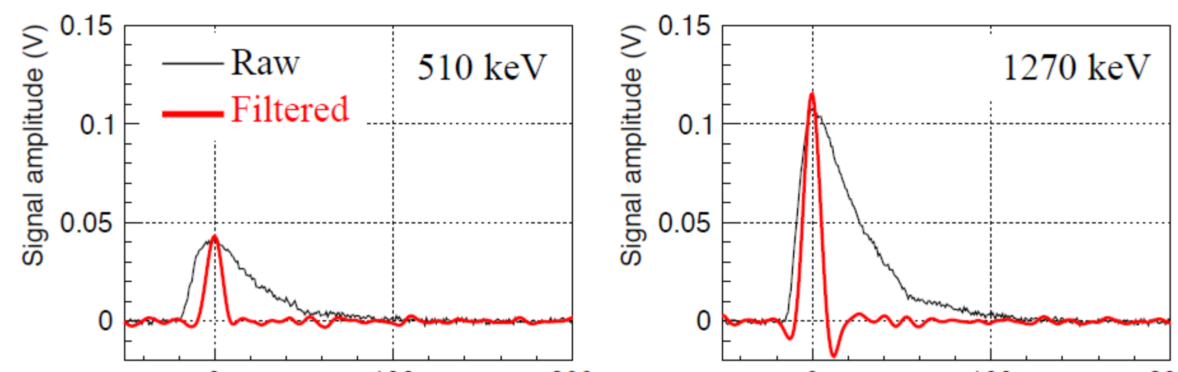


Fig. 1

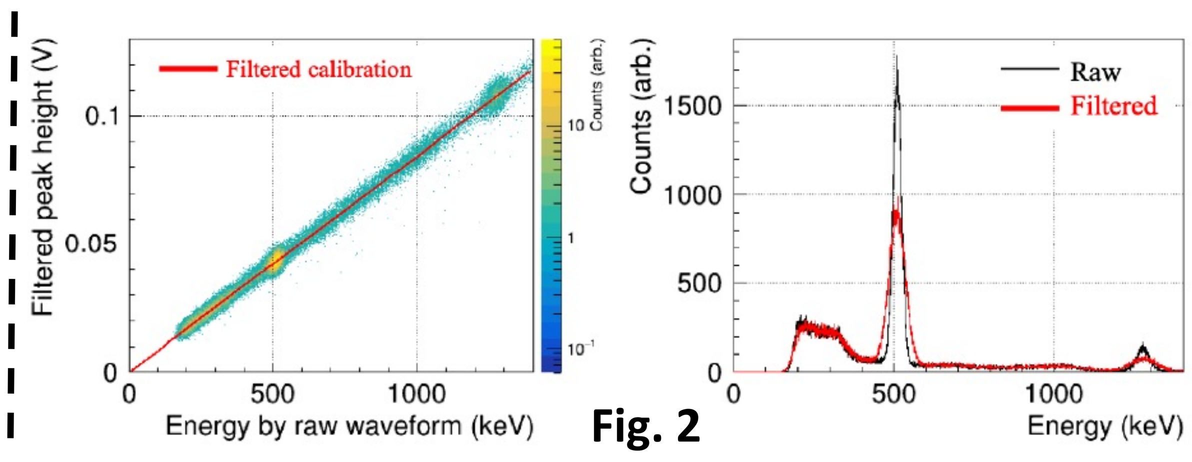


Fig. 2

The machine learning approach was implemented by the following procedure:

(1) A dataset consisting of a large portion of raw waveforms is first deconvolved using a conventional Wiener deconvolution method (Fig. 3) [1].

(2) A peak-finding algorithm measures the amplitudes and locations of the deconvolved peaks and creates a vector of the same length as the waveform with delta-like peaks that represent the locations and amplitudes of the peaks in the deconvolved waveform (Fig. 4).

(3) An architecture based on the pix2pix GAN [2, 3] is trained with the delta-like vector as the "clean" input and the raw waveform as the "noisy" input (Fig. 5).

(4) The network eventually learns to deconvolve the waveform in a way that is potentially faster than the FFT approach, with the additional ability to detect peaks in the waveform that the FFT approach missed (Fig 6).

(5) The positronium lifetime and pulse amplitudes are measured using both the Wiener deconvolution and the network-based deconvolution approaches (Fig. 7).

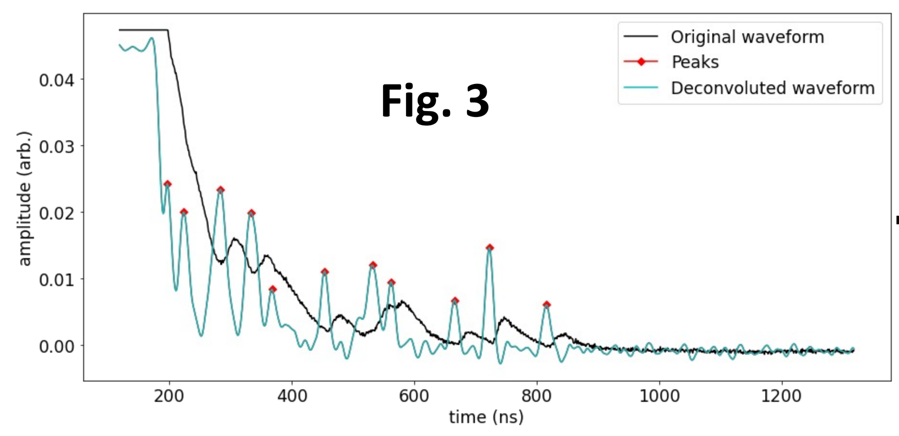


Fig. 3

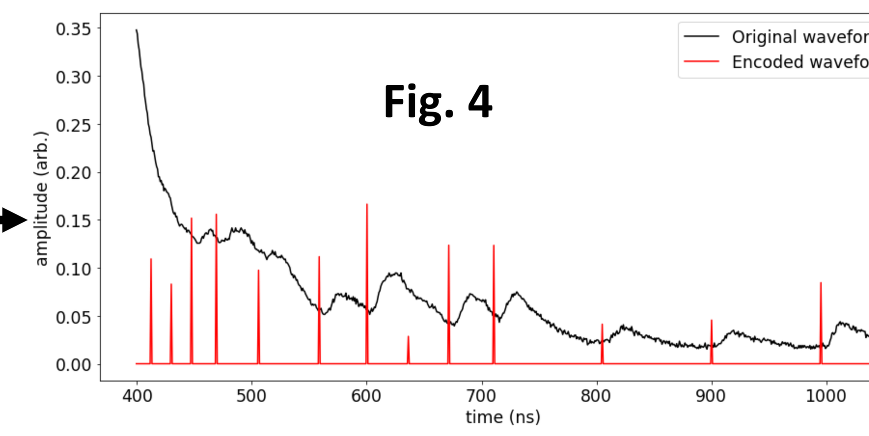


Fig. 4

The Wiener deconvolution is an FFT-based filter that deconvolutes the waveform to produce Fig. 1 [1]. Fig. 2 is an example of the delta-like peaks used to represent the arrival times and amplitudes.

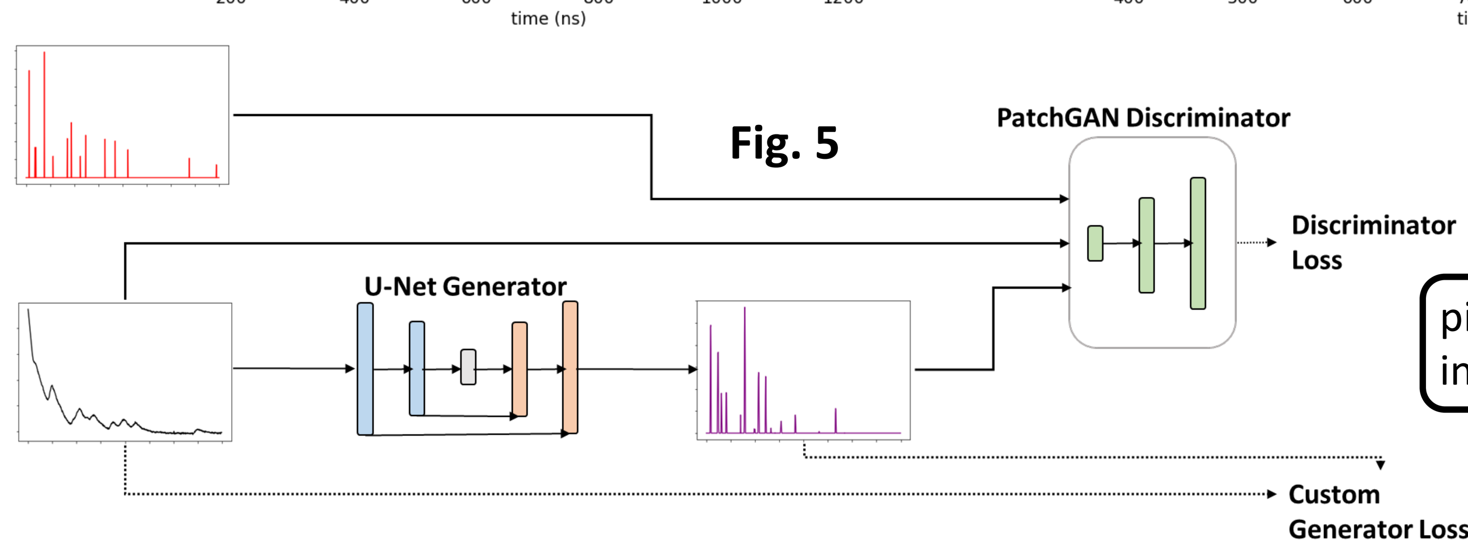


Fig. 5

pix2pix-based GAN inspired by Ref [3].

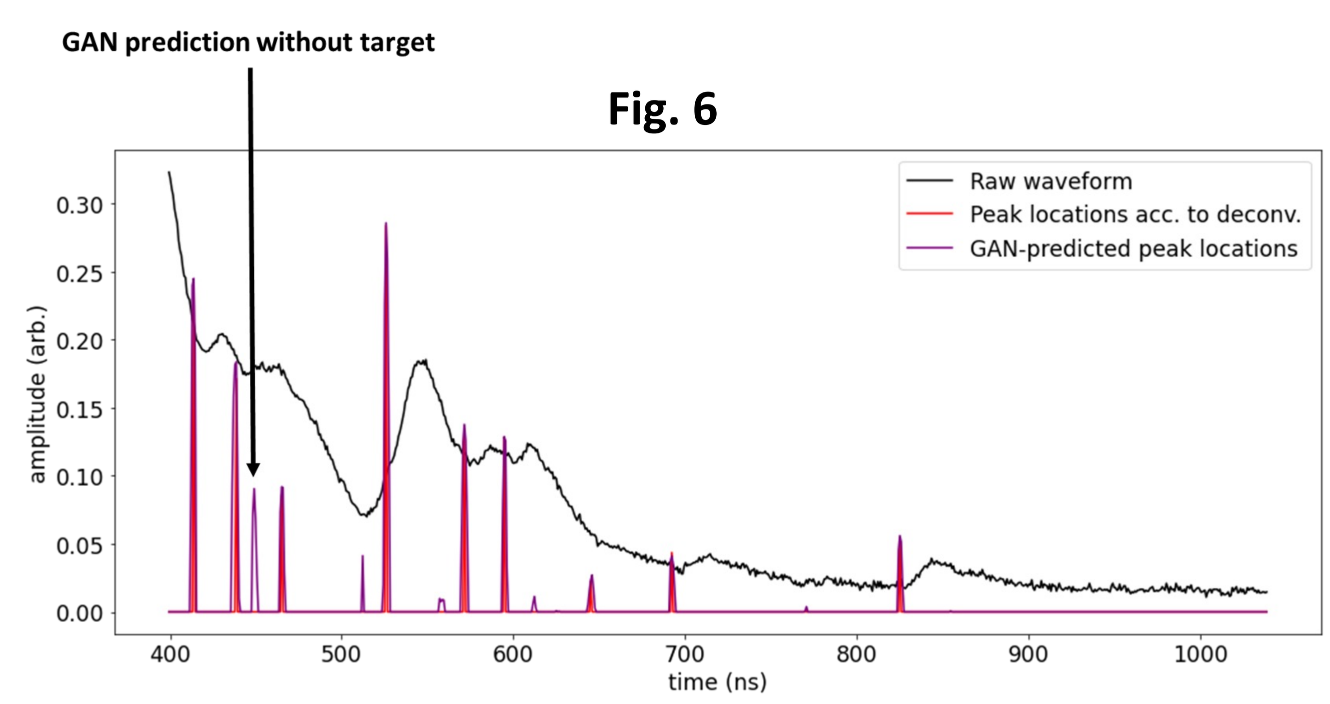


Fig. 6

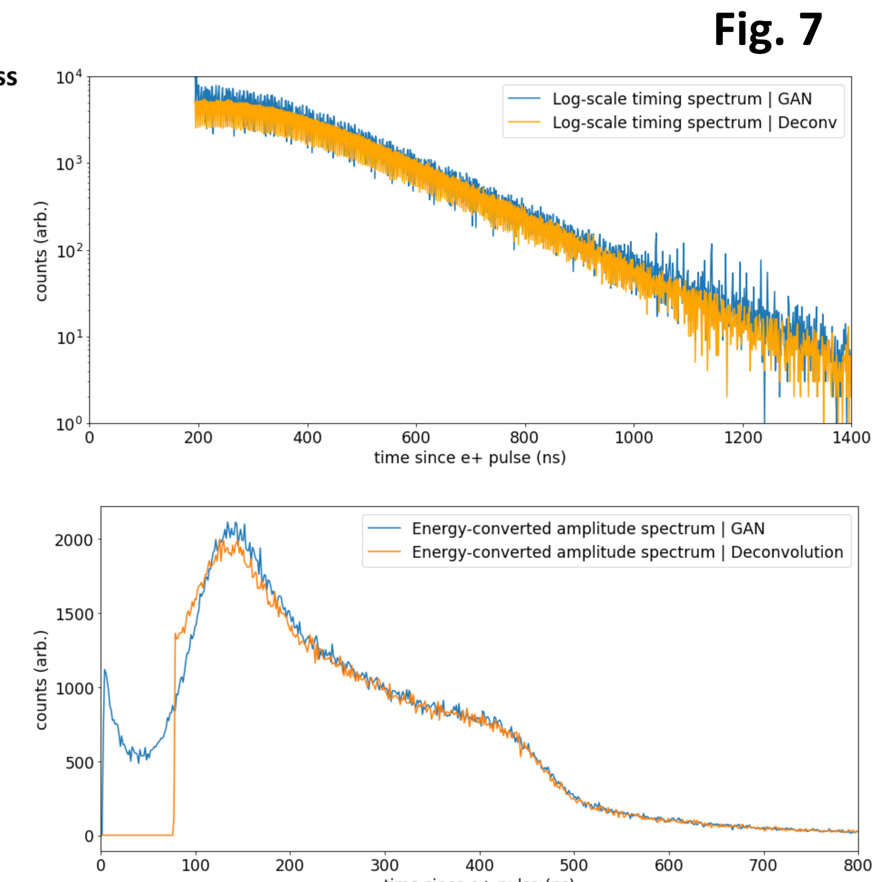


Fig. 7

Approach 2: Unsupervised Learning

(1) The raw waveforms are fed directly into the network (Fig. 8).

(2) The network-predicted signal (i.e. supposed deconvoluted waveform; Fig. 9, red line) is convoluted with an IRF (Instrument Response Function; Fig. 9 inset) predictor—a learnable parameter that is trained and learned alongside the primary signal predictor network.

(3) A background is also predicted by an autoencoder network that is provided only a small portion of the waveform as input (to detect timing shifts), and is added to the convoluted signal (Fig. 9, green dotted).

(4) The result is then provided to the loss function along with the original raw waveform and the training continues.

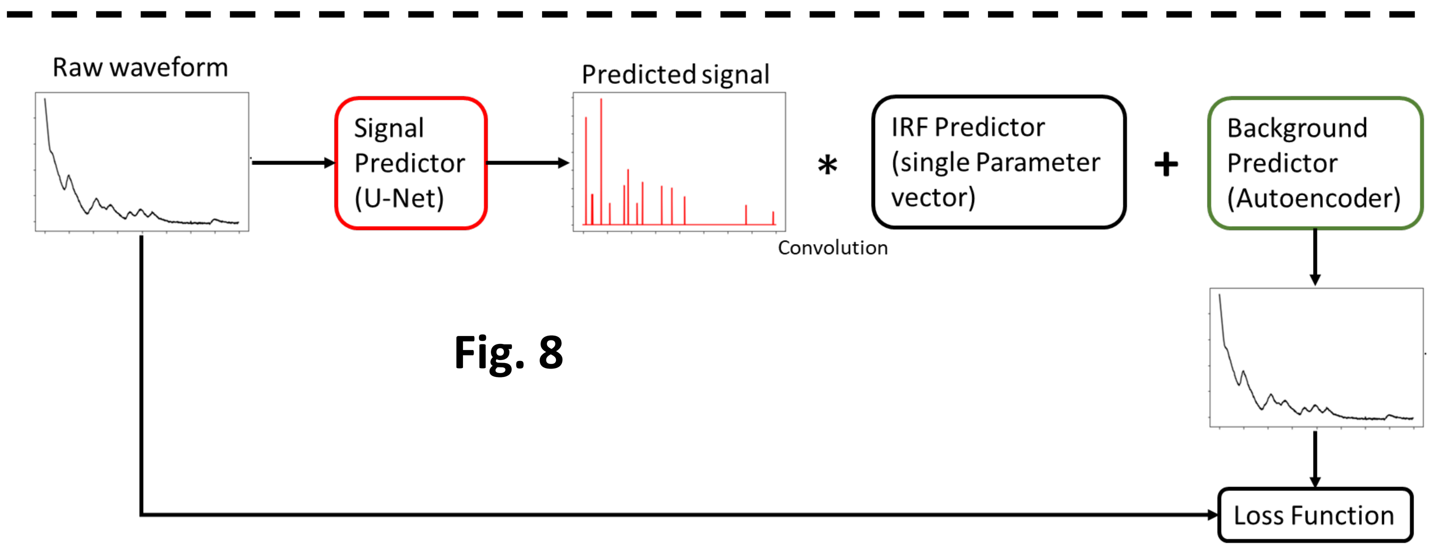


Fig. 8

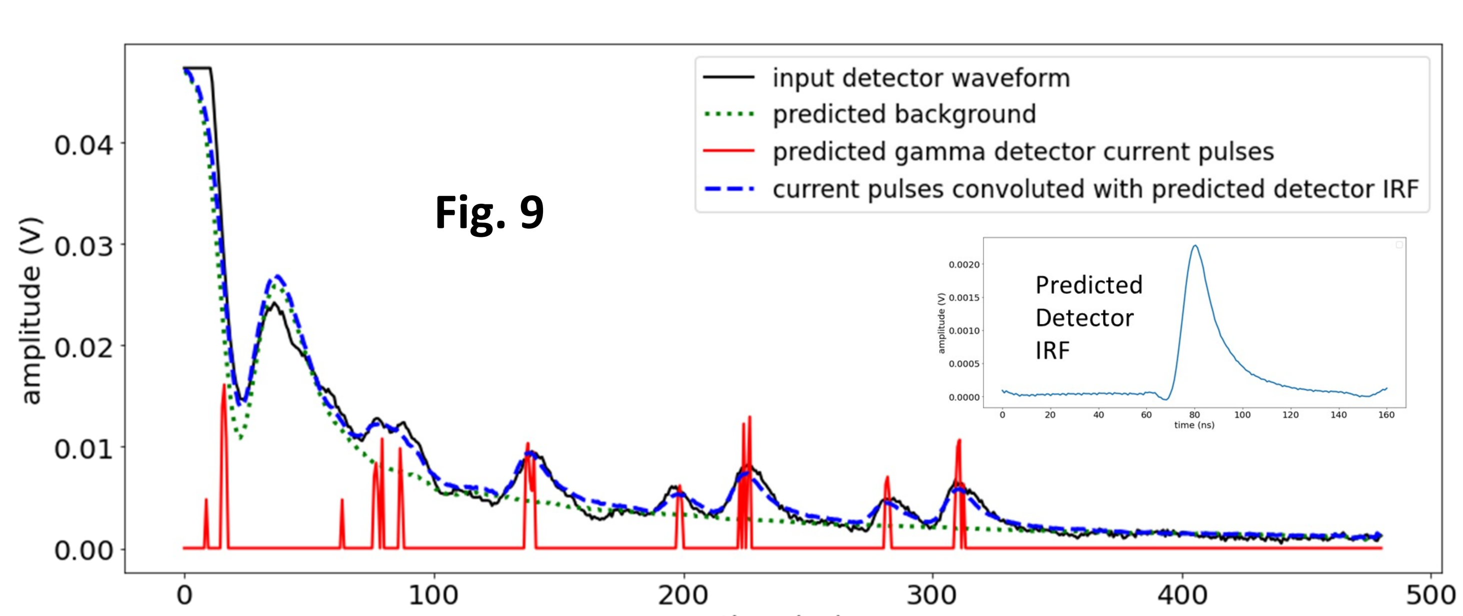


Fig. 9

This approach uses the same GAN architecture as Fig. 1 for the signal predictor network, but Fig. 4 is simplified for clarity. At the beginning of training, the "predicted signal", IRF predictor, and background predictor are all randomly initialized, and the signal predictor network gradually learns how to deconvolve the original waveform into the individual pulses as the IRF and background are learned simultaneously.

Approach 3: Unsupervised + Synthetic Data

This approach is identical to the unsupervised approach, but the waveforms are synthetic. The IRF has intentional sine wave noise added to it (Fig. 12), and the overall waveform contains Gaussian noise (Fig. 10, blue line). This approach is used to confirm that the technique is capable of learning arbitrary IRFs and backgrounds (Fig. 10, green dashed) with a relatively large number of pile-up events (see Fig. 11 for comparison). The predicted peaks are enlarged for clarity.

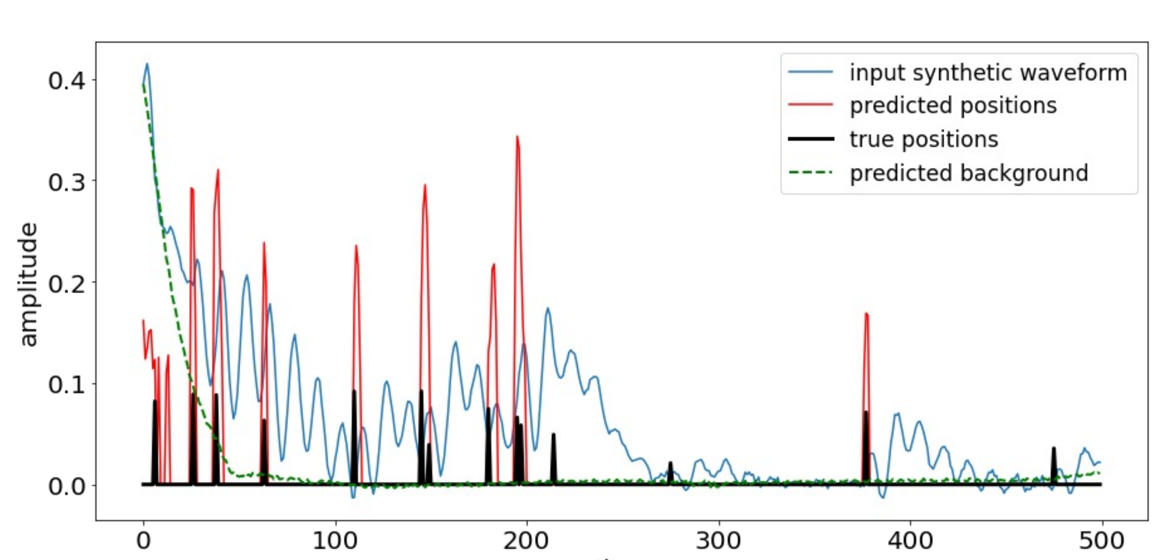
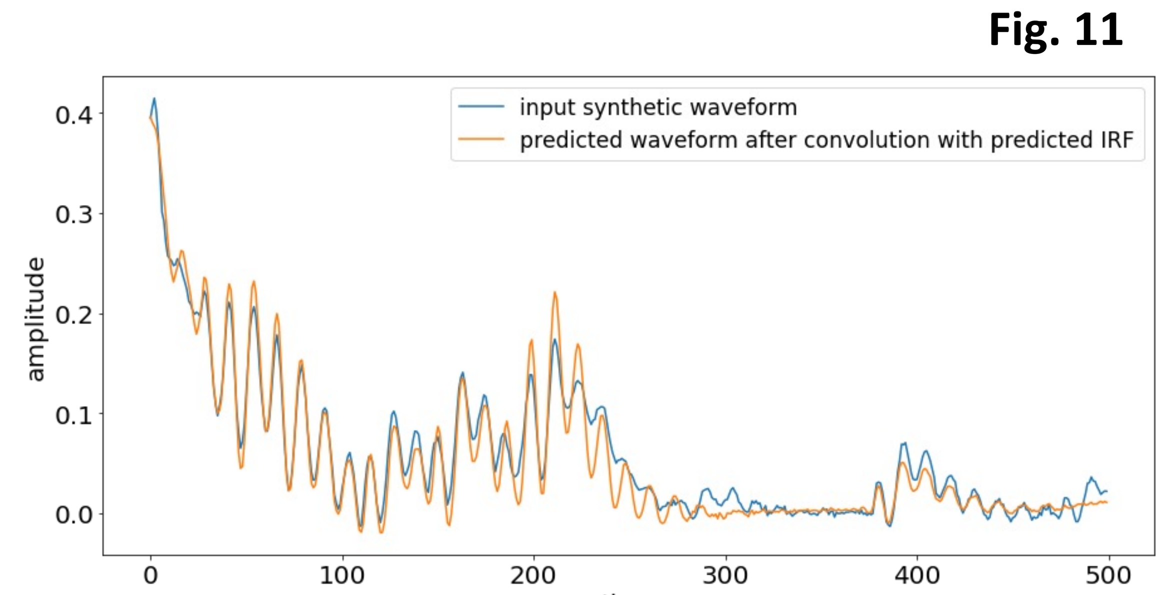


Fig. 10

Fig. 11



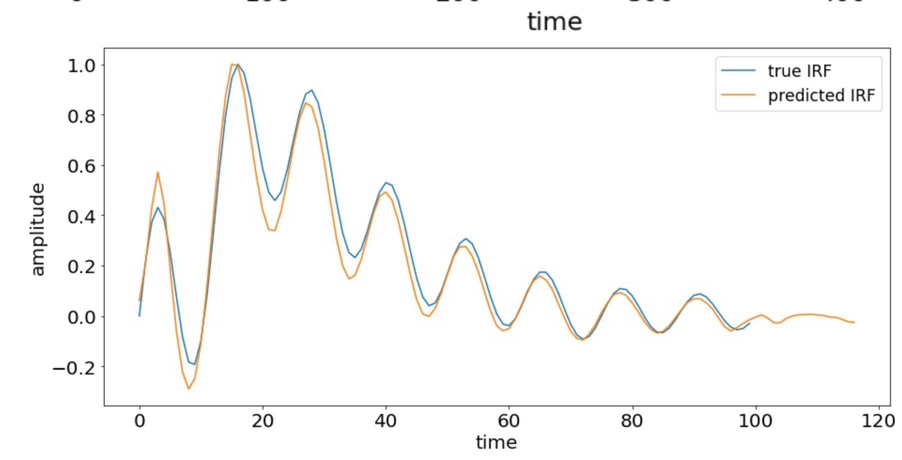


Fig. 12

References

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[2] P. Isola, et al., *Image-to-Image Translation with Conditional Adversarial Networks*, 2016 (Pix2Pix GAN)

[3] K. Schawinski, et al., *Generative adversarial networks recover features in astrophysical images of galaxies beyond the deconvolution limit*, 2017

Acknowledgements

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