FM-to-AM Effect Removal Technology of Pulse Waveform Data Based on Deep Learning

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Abstract. In the process of laser pulse transmission, amplification and sampling measurement, the amplitude-to-frequency modulation (FM-to-AM) effect caused by spectral distortion leads to peak oscillation of waveform measurement data, which is difficult to be completely eliminated by improving measurement methods. In this paper, a method of removing the FM-to-AM effect of pulse waveform data based on deep learning is proposed. After the original waveform data is de-modulated, the accuracy of waveform prediction is obviously improved. This technology can precisely remove modulated signals while retaining the key features of original data, and can well deal with various complex waveform data.

1. Introduction

Laser physics experiment has strict performance requirements for output pulse waveform of high-power laser facility. It is important to achieve high-precision power balance between beams to meet the energy and power required on target. The National Ignition Facility (NIF) of the United States achieve high performance output of 192 beams by using laser performance operation model (LOPM)[1-2]. LOPM’s main function is to predict and evaluate the performance of the NIF.

Pulse waveform is a key parameter to measure the performance of large laser facility. However, due to the amplitude-frequency (FM-to-AM) effect caused by the non-uniform transmission of phase modulated pulse spectrum, there is peak oscillation in the measured data of pulse waveform. FM-to-AM effect affects the shaping ability of laser pulse, and has a negative impact on physical experiment. There is large error in waveform prediction to evaluate laser facility’s performance by using the measured data with FM-to-AM effect directly. How to suppress FM-to-AM effect is also one of the main scientific and technological problems in laser fusion driver research in the past decade. Literature[5] studies the frequency conversion process in triple-frequency system and the effect of grating dispersion. Literature[6] analyses various factors that cause FM-to-AM effect in polarization maintaining fiber. Literature[7] systematically introduces the fundamental causes, characterization methods and influencing factors of FM-to-AM effect, and respectively introduces the research progress of FM-to-AM effect suppression technology in NIF (U.S.) and LMJ (France). The research shows that FM-to-AM effect can be pre-compensated and suppressed from the transmission level, which is difficult to eliminate fundamentally.
Based on the existing experimental measurement conditions, we consider removing FM-to-AM effect from the data level in order to improve the accuracy of waveform prediction. However, traditional algorithms[8] such as mean filtering, exponential smoothing and wavelet transform are used for the measured data, which are difficult to remove modulation signals accurately and easy to introduce new signal distortion in the operation process. On the other hand, these algorithm parameters need to be adjusted according to the specific situation of waveforms, which is tedious and time-consuming. To solve the above problems, we design an FM-to-AM effect removal model based on deep learning, which reduces the waveform prediction error by 20%. The advantage of this model is that it can effectively remove the FM-to-AM effect while retaining the key features of the original data. With strong generalization ability, the model can effectively deal with unknown waveforms.

2. Promblem

2.1. Measured waveform features

Laser pulse waveform is the main indicator to reflect the performance of the facility. The quality of the data is very important for waveform prediction and performance calculation. The typical original data of waveforms are shown in figure 1.

![Figure 1. Typical measured data of laser pulse waveform.](image)

The measured waveform data usually show the following characteristics:

- There is modulation signal with approximately periodic variation on the top of pulse.
- The descending edge of the pulse slows down, and there is a phenomenon of “tailing”.
- There is Gaussian white noise which was introduced by measuring optical path.

2.2. Waveform prediction

The data as shown in figure 1 is directly used as the input of the waveform prediction algorithm[9]. Taking the laser waveform transmission from the main amplifier to the target chamber as an example, the general flow of prediction is shown in figure 2.

![Figure 2. The original flow of target chamber’s waveform prediction.](image)

The typical waveform prediction results are shown in figure 3.
Figure 3. Prediction results of waveform using original algorithm

The error between the actual waveform and the prediction one is measured by root mean square error (RMSE)[3]. As can be seen from Figure 3, the prediction waveform is accompanied by a larger modulation signal, and the error between the prediction data and the measured data is large. The original algorithm is based on the Gain-Fluence Curve (GFC)[9], which does not consider the suppression of FM-to-AM effect. Therefore, it is necessary to remove the FM-to-AM effect from the input waveform data and improve the accuracy of waveform prediction. The design of FM-to-AM effect removal algorithm has the following difficulties:

- It is difficult to preserve the key features of waveform edge using traditional de-noising processing technology.
- The algorithm requires high adaptability to different waveform data. Traditional methods need to fine-tune various parameters according to specific waveform.
- Lack of waveform data without modulation signal. There is no corresponding data to directly evaluate the removal effect of an algorithm.

3. Approach

Aiming at the above difficulties, we design a FM-to-AM effect removal neural network based on deep learning as shown in figure 4. Deep learning can acquire the deep essential information of data by constructing a multilayer neural network and mapping the data features[10], which can overcome many shortcomings of traditional method.

Figure 4. Our proposed model (as shown in the dash lines).

3.1. Data preparation

One of the difficulties in training a de-modulation network is that there is no waveform data without noise and modulation (label data). Our solution is to simulate FM-to-AM effect by numerical method [12], and generate 20,000 pairs of waveform data with and without FM-to-AM effect. The typical simulated waveform data are shown in figure 5. Random sampling of 10% of the data as a test set.
Figure 5. Typical simulated waveform data.

Random sinusoidal FM pulse superimposes simulated modulation signal as input of the model to be trained, and the pulse without simulated modulation as output. Compared with figure 5 and figure 1, the simulated data can only partly reflect the characteristics of the real measured data.

3.2. Network architecture

We design a U-Net like network architecture similar to the one used in [11] as shown in figure 6.

Figure 6. The convolutional neural network structure based on U-net

The neural network consists of 11 convolution layers (Conv1D), 4 upper sampling layers (Up_sampling1D), 4 maximum pool layers (Max pool 1D), and Concatenate layers. The activation function of convolution layer uses ReLU. The network structure is approximately symmetrical U-shape, with contraction path on the left and expansion path on the right. Waveform data features are extracted through multiple convolution layers. However, with the increase of the number of layers of neural network, features learnt from the front layer may be lost in the process of backward transmission. Therefore, cross-layer stitching is used to realize that the data features learned at all levels are not lost.

3.3. Loss function

It is difficult to keep the smoothness near the rising and falling edges of laser waveforms in general models. Our loss function targets both FM-to-AM removal accuracy as well as reservation key feature of data:

\[
L = \frac{\sum_{i=1}^{N} |Y_i - \tilde{Y}_i|}{N} + \alpha \sum_{i=1}^{N-1} |Y_{i+1} - \tilde{Y}_i| \cdot (N-1)dt
\]  

In the formula, \(Y_i(i=1,2,\ldots,N)\) is the ith sampling point data of de-modulation waveform. \(Y_i(i=1,2,\ldots,N)\) is the ith sampling point data of waveform without modulation. \(N\) is the number of the
total sampling points of the waveform. $\alpha$ is the weight of total variation loss. $dt$ is the time interval of waveform sampling. The loss function consists of two parts: the first part of the formula is the absolute value loss which ensures that the calculation error is small and the training speed is fast. The second part is total variation loss, which aims at removing waveform burrs.

3.4. Implementation and training
Our implementation was realized in Python 3.6, using the Keras framework with Tensorflow backend. All the training and experiments were ran on a workstation with the Nvidia Tesla P100 GPU. We initialize the weights of the model using the initialization method based on Gauss distribution and use Adam [13] for optimization. After doing grid searching, we fine-tune using learning rate of $2^{-14}$ and batch-size of 4096 as training parameters. All fine-tuning is performed in one day.

4. Experiments
We apply the trained deep learning model to the actual measured waveform data. The typical result is shown in figure 7. The output of the deep learning model is smooth and without mutation. The characteristics of waveform edge are preserved while de-noising and de-modulating.

![Figure 7. Removal FM-to-AM result of measured waveform data](image)

4.1. Qualitative Comparisons
By observing the de-noising and de-modulation results of a large number of measured waveforms, the advantages of the deep learning model can be qualitatively analysed. The training data of the deep learning model are simulated data, which is far less complicated than the measured waveform. However, the trained model has strong generalization ability, which is mainly reflected in:

- The pulse width of training data contains only 2 to 3.6 ns, while the trained model can process the measured waveform with a wider range of pulse width (such as 1 to 8ns).
- The training data only contain single pulse waveforms, while the trained model can process multi-pulse ones.
- The trained model can remove the modulation which is more complex than simulated data.

Therefore, the deep learning model shows good adaptability in dealing with unknown waveforms and modulation modes, and does not need to readjust parameters according to specific waveforms as traditional methods. So it can meet the increasing demand of new waveforms in future experiments.

4.2. Quantitative Comparisons
The input data of waveform prediction in figure 3 are processed by the deep learning model, and then used for prediction calculation. The result is shown in figure 8.
In Figure 8, the RMSE of waveform prediction decreased from 141.2 to 74.6 and 154.3 to 52.3, respectively. The prediction error of the new method decreases obviously compared with the old method. We randomly selected 3 months of experimental data for statistics. The data of 167 shots × 48 beams are counted in all. After the FM-to-AM effect of waveform data is removed by deep learning model, the prediction waveform error decreases by about 20% as a whole (shown in Table 1). This further confirms the rationality of the model in this paper.

Table 1. A statistic of RMS reduction by using new method.

| Month | Num of shot | RMS average decline rate |
|-------|-------------|--------------------------|
| 2018.5 | 68          | 21.7%                    |
| 2018.12 | 53          | 19.2%                    |
| 2019.3 | 56          | 22.8%                    |

5. Conclusion
In this paper, a deep learning model to remove FM-to-AM effect of waveform data is proposed. It is used to process measured data and as waveform prediction’s input. The prediction error is greatly reduced as a result. Compared with traditional methods, the advantages are: high-precision de-noised and de-modulated are achieved while retaining the key features of waveform; the model can process various types of waveform without the need to adjust according to actual waveform. This study lays a technical foundation for the intellectualization of operation and maintenance of large laser facility, such as performance prediction and evaluation.

References
[1] Williams W. H., Auerbach J. M., Henesian M. A., et al. (2004) Optical Propagation Modeling for the National Ignition Facility. Proceedings of SPIE - The International Society for Optical Engineering, 5341:66-72.
[2] Shaw M., Williams W., House R., et al. (2005) Laser performance operations model (LPOM): a tool to automate the setup and diagnosis of the National Ignition Facility. Proceedings of SPIE.
[3] Glenzer S., Jones O. (2001) 3ω power balance procedure on the NIF. doi: 10.2172/15013548.
[4] Browning D. F., Rothenberg J. E., Wilcox R. B. (1999) The issue of FM to AM conversion on the National Ignition Facility. Proceedings of SPIE - The International Society for Optical Engineering, 3492.
[5] Hocquet S., Penninckx D., Bordenave E., et al. (2008) FM-to-AM conversion in high-power lasers. Applied Optics, 47(18):3338-49.
[6] Penninckx D., Beck N., Gleyze J. F., et al. (2006) Signal Propagation Over Polarization-Maintaining Fibers: Problem and Solutions. Journal of Lightwave Technology, 24(11):4197-4207.
[7] Xu D. P., Zhang R., Tian X. C., et al. (2017) Progress on FM-to-AM Effect and Its Suppression in High Power Laser Driver. Laser & Optoelectronics Progress, 54(2): 020005.

[8] Zhang Z. T., Zhu J. J., Kuang C. L., et al. (2014) Comparative Study and Improvement on Several De-noising Methods for Different Noise. Journal of Geodesy and Geodynamics, 34(1): 127-130.

[9] Wang W. Y., Zhao R. C., Su J. Q., et al. (2010) Preliminary Laser-Pulse-Shaping on Technical Intergration Line. Acta Optica Sinica, 30(4): 1051-1054.

[10] Chen R. M., Sun S. L. (2017) Automatic Extraction of Infrared Remote Sensing Information Based on Deep Learning. Infrared, 38(8): 37-43.

[11] Ronneberger, O., Fischer, P., Brox, T. (2015) U-Net: Convolutional Networks for Biomedical Image Segmentation. International Conference on Medical Image Computing & Computer-assisted Intervention.

[12] Wang W., Li P., Li H., et al. (2014) Analytical Quantification of FM-to-AM Effects in Frequency Conversion. Chinese Journal of Lasers, 41(1): 0102009.

[13] Kingma D. P., Ba J. (2014) Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980.