Laser Pulse Duration Optimization with Numerical Methods

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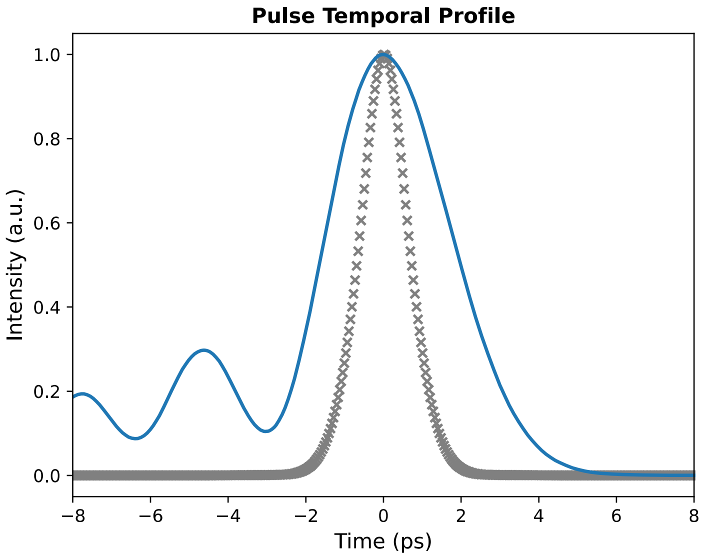
Introduction

Obtaining short and sharp laser pulses is crucial for running high-efficiency physical laser systems that would reach really **high intensities**. The control operation aims at obtaining a shape close enough to the shape of the **transform limited pulse.**



We build control feedback loop between pulse shaper and pulse duration measurement device (FROG) and tested it on a semi-physical model using several different loss functions and three optimization algorithms:

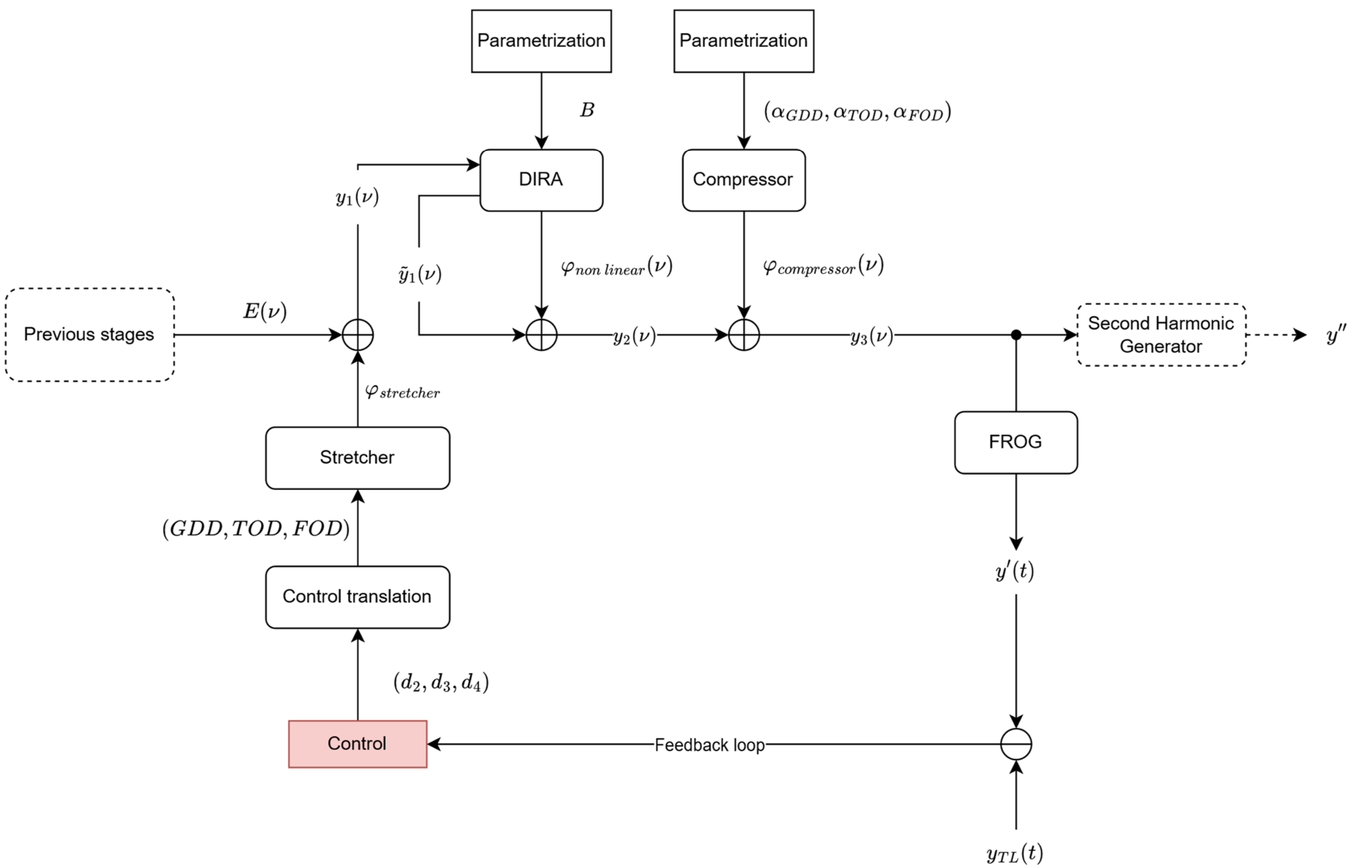
1) **Bayesian Optimization.**
2) **Differential Evolution.**
3) **Gradient-Based Optimization (AdaGrad).**

Semi-Physical Model

Each stage of the process has been mathematically described and a customized simulator has been built to reproduce the system dynamics for various values of the control applied.

Despite evident differences between the real world and our model, we found this semi-physical model to be a **good approximation** of the actual machinery.

L1 Pump Laser Semi-Physical Model



Loss Function

Loss function 0: Mean Squared Error (MSE) between target and controlled pulse

Loss function 1: Weighted-Mean Squared Error between target and controlled pulse

Loss function 2: Mean Squared Error only for values which are numerically non zeros

Loss function 3: Weighted sum of (2) and mismatch in terms of area underlined by the controlled pulse

Loss function 4: Weighted sum of (2) and minimization of sum of first-n peak width

Loss function 5: Weighted sum of (2) and difference of FWHM

Loss function 6: L1 Manhattan Norm

Bayesian Optimization

Exploration of the search space is fundamental to achieve good results in terms of final solution. However, the need of **exploration itself is a very dangerous** aspect when it comes down to the physical application of this algorithm in the real world.

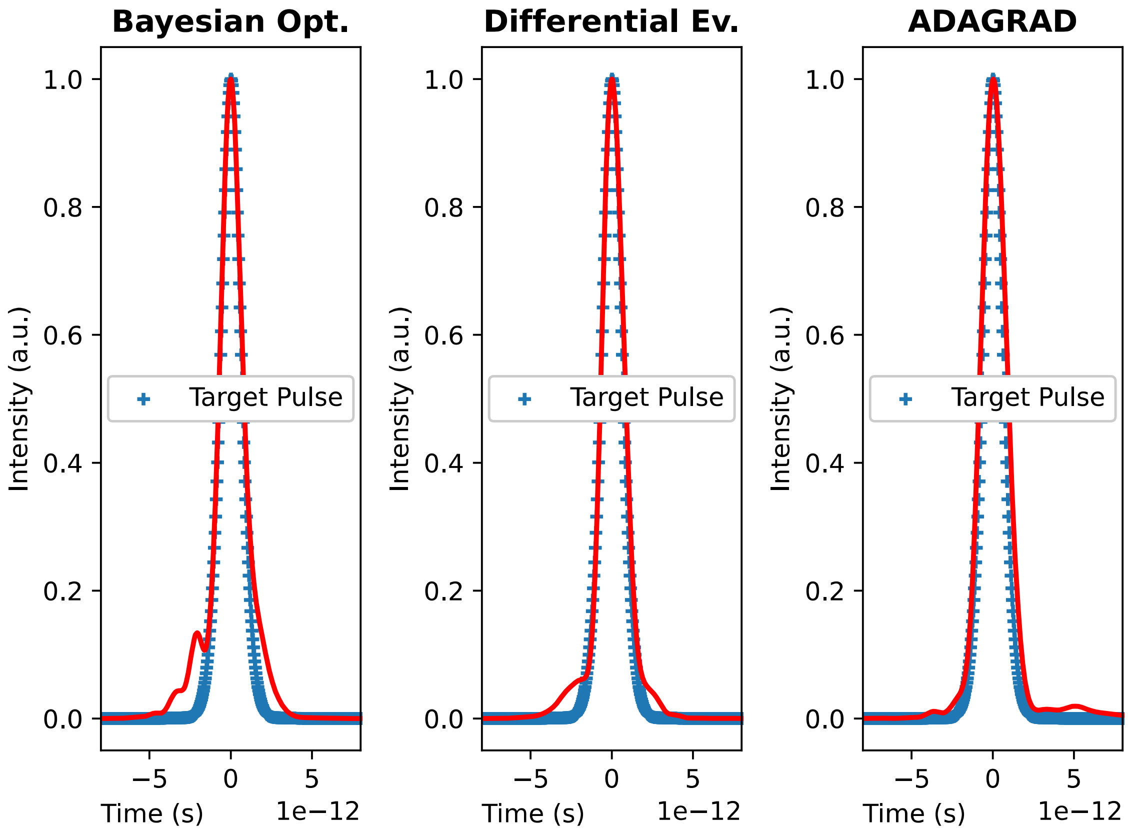
Differential Evolution

Despite this algorithm being well suited for a variety of different applications, it does require **a large number** of function evaluations. Furthermore, even if it is commonly used to achieve good neighborhoods of the optimal solutions, **it can get stuck in local minima** as no notion of momentum is typically applied to this algorithm.

AdaGrad

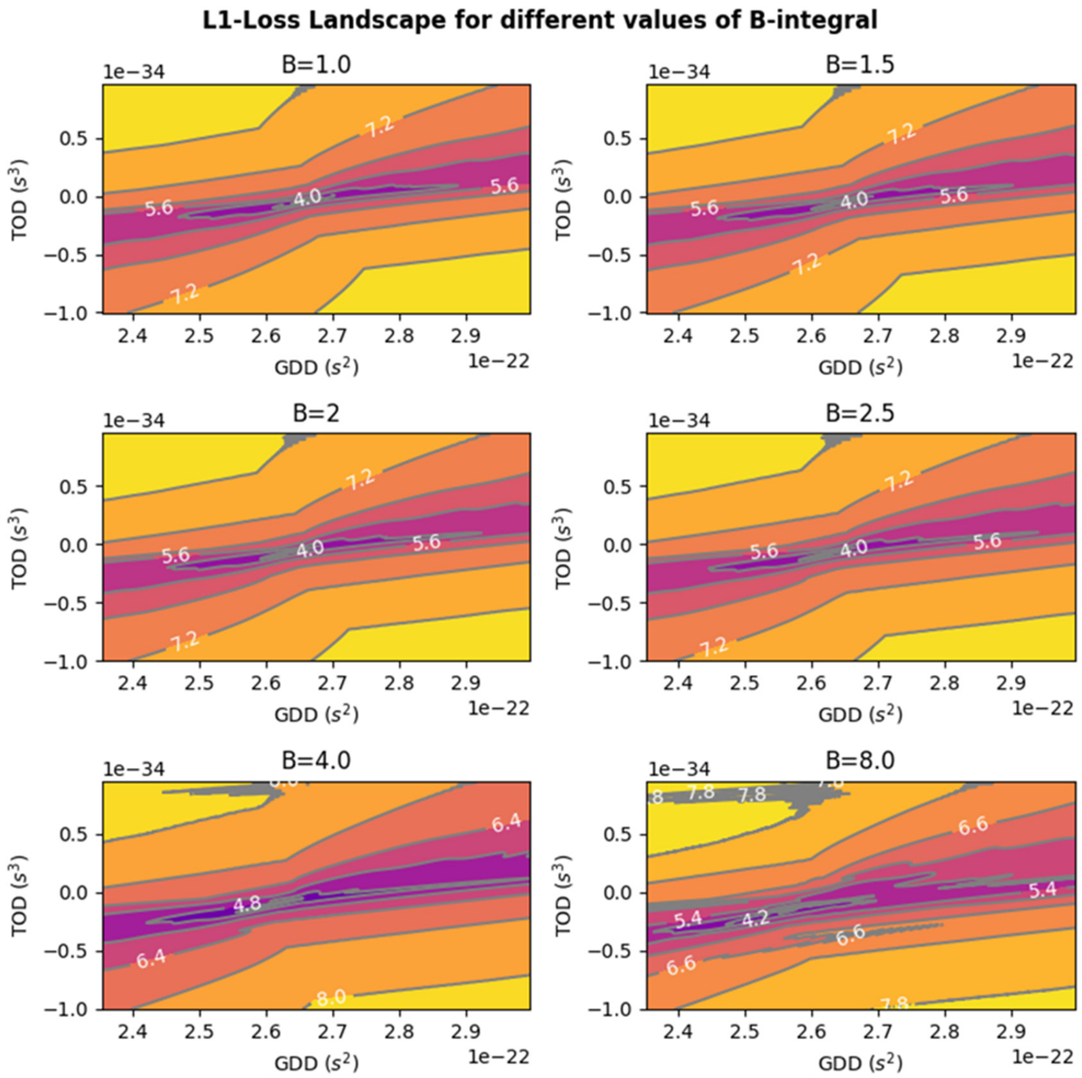
Despite the theoretical guarantees of this algorithm, its practical application is limited to the case in which the output is differentiable with respect to the input (**this is also possible if a DNN is built to approximate the laser model**).

Results



Algorithm	Number of func. evaluation	Final MSE
Bayesian Opt.	150	$2.6x10^{-5}$
Differential Ev.	4000	$1.5x10^{-5}$
AdaGrad	3000	$4.9x10^{-6}$

Results


L1-Loss Landscape for different values of B-integral
B=1.0
B=1.5
B=2
B=2.5
B=4.0
B=8.0
TOD (s^3)
GDD (s^2)
1e−34
1e−22

Conclusions

The algorithms have been proven to converge to desired shape under acceptable threshold. The algorithms differ in numbers of function evaluation and practical applicability. To achieve smart self-tuning laser we need a technology which is:

- **Deployable** in the real world
- **Robust to a imprecise knowledge** of relevant parameters for the dynamics of the system
- Efficient and **scalable to various level of control**

Thank you for your attention