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FEED-FORWARD NEURAL NETWORK BASED MODELLING OF AN ULTRAFAST LASER FOR ENHANCED CONTROL

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Abstract

The applications of machine learning in today's world encompass all fields of life and physical sciences. In this paper, we implement a machine learning based algorithm in the context of laser physics and particle accelerators. Specifically, a neural network-based optimisation algorithm has been developed that offers enhanced control over an ultrafast femtosecond laser in comparison to the traditional Proportional Integral and derivative (PID) controls. This research opens a new potential of utilising machine learning and even deep learning techniques to improve the performance of several different lasers and accelerators systems.

INTRODUCTION

Machine learning (ML) and the advent of deep learning have reduced solving several complicated problems into a few lines of code. The ability of these techniques to be able to handle high complexities and N-dimensionality, allow ML to solve several critical optimization problems. Several fields of research today rely on these algorithms. From areas of research such as computer vision [1] to life sciences such as computational biology [2], ML has been a reliable tool of research. Within the field, neural networks lead the forefront in applicability as compared to other ML based algorithms. The ability of neural networks to be able to capture any mathematical operation makes it one of the most versatile computer algorithms for prediction and classification.

Particle accelerators are used to produce beams of charged particles using electromagnetic fields. The particle beams are then used for a diverse range of applications, ranging from material research to treatment of cancer for example. Particle accelerators are typically very complex systems which have several subsystems, all of which have a nonlinear rule governing them. Theoretical modelling of these systems is a very cumbersome process due to the complexities that come with it. Without any steady state at any instance of operation, theoretical prediction of control and automation fails to reach the practical values.

This research is done in the context of electron beam accelerators, where the electron production is done via photoelectric effect, by shining a laser on a photocathode. The electron production process depends on the photocathode material but also on the high-power laser used to irradiate the cathode [3], on the shape of the laser beam shining on the photocathode. The laser beam profile can be shaped using for example a deformable mirror, giving us the capability of accurately controlling the driving laser beam to maximize electron beam parameters, thus maximizing the efficiency of the experiment.

In general, our neural network model is designed to optimize the actuators controlling the deformable mirror [4], and therefore the laser beam profile shining on the photocathode so that properties of the electron beam downstream are optimized, e.g., higher beam current or lower beam emittance. The beam emittance is particularly sensitive to the initial electrons produced at the photocathode, and in general it grows as the beam travels through the accelerator, thus emphasising the importance of having accurate control on the laser system, and the motivation of using ML to further push the accelerator performance, particularly in low energy electron beam experimental lines.

In this paper, we implement a machine learning based algorithm in the context of laser physics and particle accelerators. For this work, we use the low-jitter DAZZLER input parameters to produce an optimised time-bandwidth product as output. The corresponding Frequency Resolved Optical Grating (FROG) outputs were used to train the network. The FFNN model formulated shows a high accuracy in comparison to the other state-of-the-art control techniques. This opens a new potential of utilising ML and even deep learning techniques to improve the performance of several different lasers and accelerators systems.

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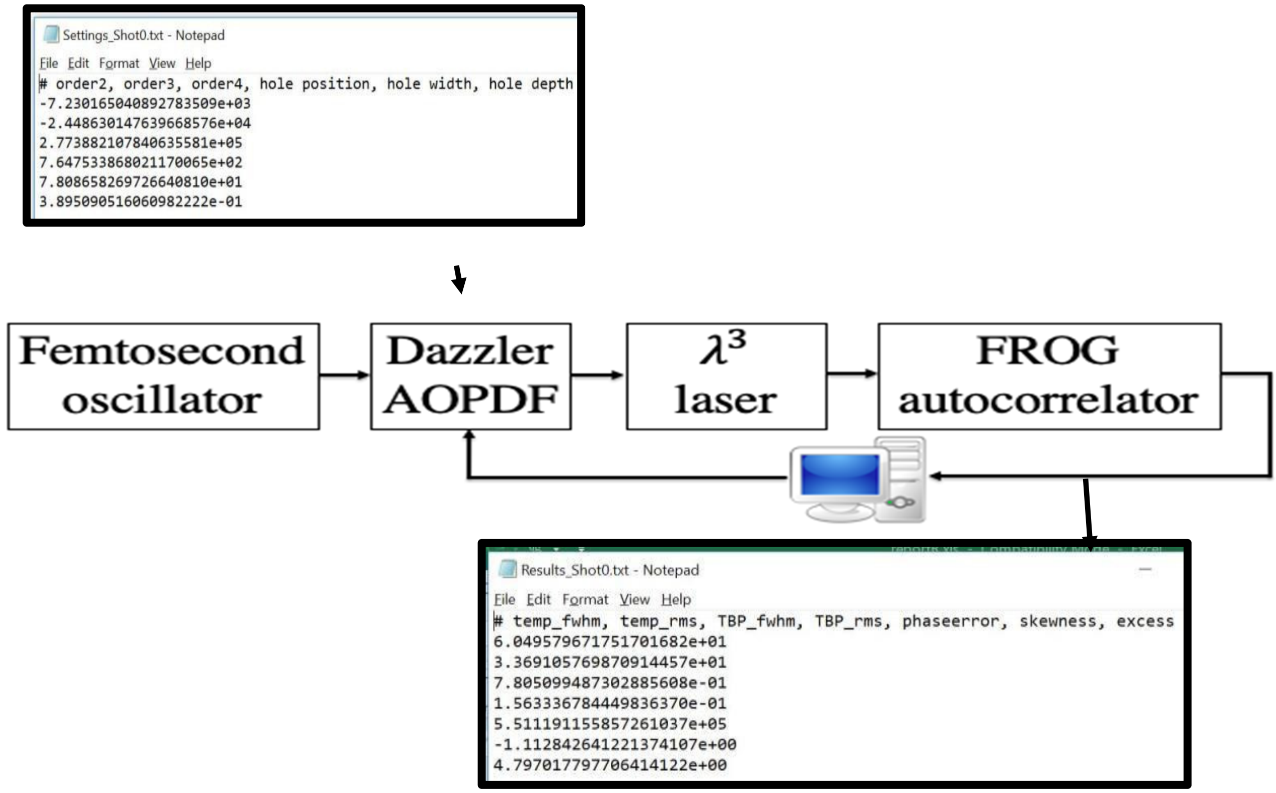

Fig. 1: A schematic of the Experimental setup. As can be seen, there are 6 input parameters which after modelling and input-output mapping predict the temporal Full width half maximum as output.

Research Methodology

The development of the model, including the laser control and parameter selection along with training and testing of the algorithm was performed in line with the experimental setup reported in [5], where a genetic algorithm was used to find the solution of optimised parameters for 37 actuators, we try to develop an iterative neural network as can be seen in Fig. 1. In a proposed neural network, we take the experimental parameters that we obtain from DAZZLER settings. These parameters are the second, third and the fourth order phases, the hole position, width and the depth of the laser pulse that is provided by a femtosecond laser cavity. The output of the neural network consists of the FROG parameters that typically have seven characteristics. These characteristics include temporal full-width-half-maximum (Temp-FWHM), the temporal root mean square (RMS), the time-bandwidth product FWHM and RMS, the phase error, skewness, and the excess. Typically, any laser pulse can be expressed and described using amplitude and phases. Typically, by creating a hole in the laser spectrum before it enters the amplifier can lead to laser pulses with large bandwidth and ultrashort pulse duration. The amplitude and phase of the pulse can be further tuned and explicitly perturbed with the help of the hole parameters which are the hole position, width, and depth.

For our neural network model, we try to put more emphasis on the temp-FWHM. In that context, instead of optimising all seven FROG parameters, only the temp-FWHM was set as output parameter in the pipeline. Due to this, the other trade-off which existed during the optimisation of all parameters was neglected and accuracy of predictions of temp-FWHM was improved. Furthermore, in addition to the input/output feature selection and model definition, the training function for the FFNN was chosen to be the Levenberg-Marquardt algorithm [6].

The modelling of the neural network and its training was done with the help of 2000 laser pulse shots, each corresponding to a single data point in data set. Out of these 1000 laser pulse shots were fed to the neural network iteratively to train the neural network. The rest of the data points were reserved for testing of the model. For ease of calculating and for the proof of concept, the neural network was made with two hidden layers equipped with 10 and 5 neurons, respectively. After the entire training process with the help of the Levenberg-Marquardt algorithm, the target estimation and the performance measurement were calculated. To measure the performance, we use the mean

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square error function, which is usually a standard way of expressing the error in prediction of the output in neural networks.

RESULTS AND DISCUSSION

Here we discuss preliminary results and outline the future work with this approach of using ML to solve neural network-based laser and particle accelerator control optimisation.

After the training of the model with a total of 1000 points, we see the error rates for most of the test data is nearly 0. Moreover, with a high number of epochs we can further tune the error of prediction. There can be significant increase in the accuracy, had we used more hidden layers. In the direction of future prospective study using our proposed neural network, we can work with optimising the total number of layers that would be required for sufficiently correct prediction of the TBP-FWHM, for a given set of computational constraints. Moreover, the ability to handle high level computational complexities can be appreciated through this process. In comparison to the other optimisation methods such as using extremum optimisation of parameters [7], our neural network performs faster and more efficient.

Further work using multiple layers using a higher number of data points in underway to better understand the input/output relationship. Moreover, through the help of a large dataset, an open source-based tool can be developed which could automate the entire process of parameter optimisation of such systems for enhanced control.

CONCLUSION

In summary, with the help of machine learning and deep learning techniques, the modelling of an ultrafast pulse laser was performed. In this context, with the help of a neural network, the correlation between the DAZZLER input parameters and FROG output parameters was investigated. Further, a numerical prediction model to get the time-bandwidth product of a laser pulse in the presence of a parameter-tuneable hole in the laser spectrum was reported. The results show that neural networks outperform the state-of-the-art methods of control like PID optimization of ultrafast pulse lasers. Further work is underway, with an effort towards experimental demonstration of the neural network. Moreover, more detailed results along with numerical results of the FFNN, will be presented at the conference.

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