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Kai Jin, Yimin Hu, Wei Lu, Shukui Zhang, "Laser beam control using machine learning technology for particle accelerator," Proc. SPIE 11997, Optical Components and Materials XIX, 119970M (4 March 2022); doi: 10.1117/12.2608311

SPIE.

Event: SPIE OPTO, 2022, San Francisco, California, United States

Laser Beam Control Using Machine Learning Technology for Particle Accelerator

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ABSTRACT

The Pockels Cells play important role in generating helicity-flipping polarized laser beam to be used in high energy electron beam accelerator facility. Due to exceptional requirements for ultra-stable electron beam in modern nuclear physics experiment, the operation of Pockels Cells which are key components to generate stable electron beam becomes critical. However, since the operation of Pockels Cell, which usually work in pair, involves beam alignments up to 12 degrees of freedom, it requires extremely complicated controls to maintain the stable output beam through whole operation time of accelerator. In this paper, we combined the machine learning method with the Pockels Cells control system, automatically collected data of Pockels cells optical properties such as polarization extinction ratio (PER), beam position, optical intensity asymmetry, etc., at different orientation angles and physical potions, and built an artificial neural network which can determine the optimal position of Pockels Cells. The trained artificial neural network can predict the PER, intensity asymmetry, beam position difference with a mean agreement around 95%, which makes it possible to find the optimal yaw/pitch/roll angles and physical positions of the Pockels cells in a short time. This technology can also be translated to alignments of devices in other laser systems such as high energy ultrafast oscillators and amplifiers.

Keywords: Pockels Cell, Accelerator, Neural Network, auto-alignment, machine learning

1. INTRODUCTION

Polarized electrons have long been used in the study of atomic and condensed matter physics. The polarized electron beam has been demonstrated to be a key factor in the success of many high-energy physics programs and nuclear physics programs in Department of Energy national labs such as Stanford linear accelerator center (SLAC) and Jefferson Lab's Continuous Electron Beam Accelerator Facility (CEBAF). The polarization of electron beam is determined by the polarization state of the incident laser beam, which is controlled by the helicity-flipping Pockels cell (PC) system, as shown in **Figure 1**. In the latest Parity experiment in Jefferson Lab, random sequence of high voltage PC driving pulses with swing of control voltage between $V_{-\pi/2}$ and $V_{\pi/2}$ will generate circularly polarized laser light in complementary helicity states. The repetition rate is 30Hz with rising time of each pulse in the range of 100μs [1]. However, the helicity-correlated (pulse-to-pulse) differences in the beam's intensity, energy, position, angle, or spot size can generate false asymmetries in the scattering rate into the detector that can bias the measurement of the physics asymmetry [2]. Tremendous efforts have been made to understand, and suppress the asymmetries arising from effects mentioned above and it is very obvious the Pockels Cell is the key component in generating the desired stable laser beam and electron beam in the injector of the accelerator.

The Electro-optic modulator used in our PC system is based on double potassium di-deuterium phosphate (DKDP) crystals that are 90° rotated between them. The DKDP modulator is transversely modulated that requires much lower driving voltage compared with longitudinal modulated crystal like RTP to balance the requirement for both EO-crystal and driver, therefore improve performance of the PC system. In a transverse system, the strength of applied electric field is independent to the crystal length, and reversely proportional to the crystal width. Its driver voltage is governed by the ratio between crystal width (W) and crystal length (L). A modulator with larger clear aperture will require higher drive voltage which can also be reduced by increasing the crystal length. In dual-crystal arrangement, the

Optical Components and Materials XIX, edited by Shibin Jiang,
Michel J. F. Digonnet, Proc. of SPIE Vol. 11997, 119970M
 · doi: 10.1117/12.2608311

crystal's inherent birefringence cancels each other and crystal pair behaves as a zero order wave plate at modulation, therefore greatly improves the stability of the phase modulation. The polarization of the light at the output of the crystal is circular when the two components are 90° ($\pi/2$) out of phase. The direction of circular polarization can be flipped from clock-wise to counter-clock-wise when their phase delay is switched between $\pm \pi/2$.

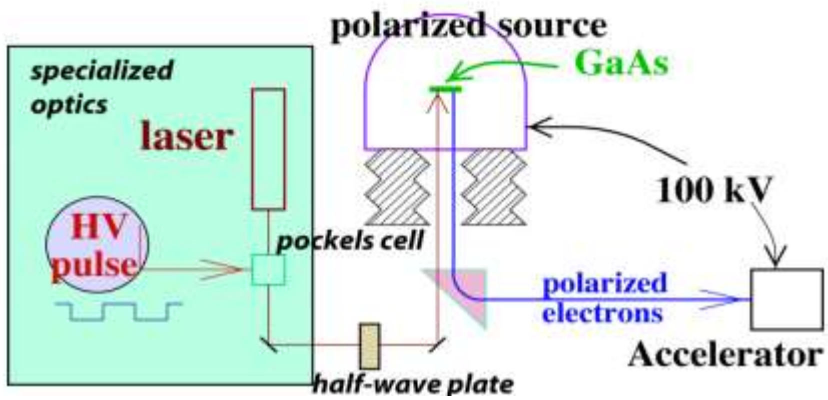

Figure 1: The schematic of the injector setup at JLab. The Pockels Cell (PC) was used to convert linearly polarized light into circularly polarized light. The wavelength of the source laser is 780nm**.**

The DKDP crystals we used in the system have the size of 4mm×4mm×40mm and two cells are mounted in home-made control stages as shown in Figure 2. To align the translation and angle orientation, five pico-motors have been used for each cell. We found in the experiment that the translation in z direction is not important and thus the control in z direction is omitted. Nonetheless, we still have 10 degrees of freedom total to control in our PC system.

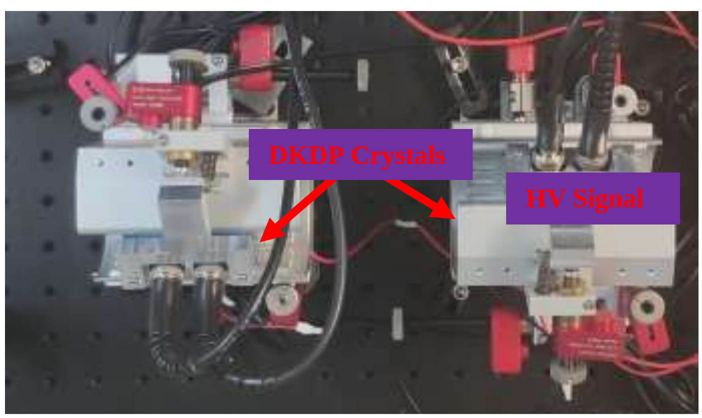

Figure 2: Dual-DKDP PC system with total of 10 degree of freedom controls.

Typically, the experiments conducted in national lab take weeks or even months and from time to time, the operators will conduct extensive tuning of PC system each time even the PC system is optimized at the beginning of the experiment. Parameters involved in tuning the PC system are orientation angles, the applied control voltage, the ambient temperature, etc. Though experienced operators can become adept at handling so many parameters quickly, at some point, they will not be able to efficiently and effectively achieve good performance. For example, a traditional tuning of PC system is done with manual efforts and takes quite a long time: operators need to first roughly align the back-reflection from the cell window, and then minimize the residual linear polarization for both helicity states to below 5% with a spinning linear polarizer using polarization induced transport asymmetry (PITA) voltage, overall roll and relative roll. The more precise alignment is done by minimizing intensity asymmetry in one position plane with PITA voltage then intensity asymmetry in another position plane with relative roll. And finally zero out the steering effects and analyzing-like position difference with quadrant position detector (QPD). All of these steps, even for a PC system with only one crystal, will take significant amount of time. For a typical PC system that has two separate crystals and each crystal has five degree of freedom, the alignment is extreme time consuming [3]. To solve the problem, we developed an auto-alignment system supported by machine learning technology and greatly reduce the time spent on commissioning of the system. For the work presented in this paper, we mainly focus on the automatic alignment of orientation angle of each PC crystal, which involves five degree of freedom: x/y translation and yaw/pitch/roll in rotation. Adding more control parameters like applied voltage and ambient temperature into the automatic alignment system is on-going and will present later.

2. SCAN AND COLLECT DATA

For the dual-crystal PC system which has five degree of freedom for each crystal, there are a lot possible combinations of the rotation angles of the two cells. To understand the relationship between the orientation angles and the characterization result (e.g., polarization extinction ratio (PER), intensity asymmetry, beam position difference), we need to scan through these possible orientation angles and collect the Pockels cell system characterization information at each location.

One limitation of our system is the piezo-drivers used to move the Pockels cells. We used five Newport 8301NF Picomotor on each mount to change the Pockels cell's x/y translation and yaw/pitch/roll rotation angles. Unfortunately, this piezo-driver is an open-loop model, so it has hysteresis and drift issue, which means the repeatability of this piezo-driver is not good. And due to the limited space on the cell mount, we cannot replace it with a close-loop model. To overcome this issue, we developed a position feedback system to precisely control the motion of the piezo-drivers: we attached a mirror to the side surface of each Pockels cell, and use a Thorlabs CPS635F Focus Laser Diode Module to point at the mirror, and a Thorlabs PDQ80A beam position sensor is placed at the reflected laser spot. The feedback system is shown in Figure 4. When the piezo-driver drives the Pockels cell to make displacement in any direction, the reflected laser spot will also move at certain distance. We monitor the motion of the reflected laser spot to avoid the drawbacks of the open-loop piezo-drivers: instead of commanding the piezo-driver to move a certain number of steps, we only need to make sure the reflected laser spot moves in either x or y direction for a certain distance from point A to point B.

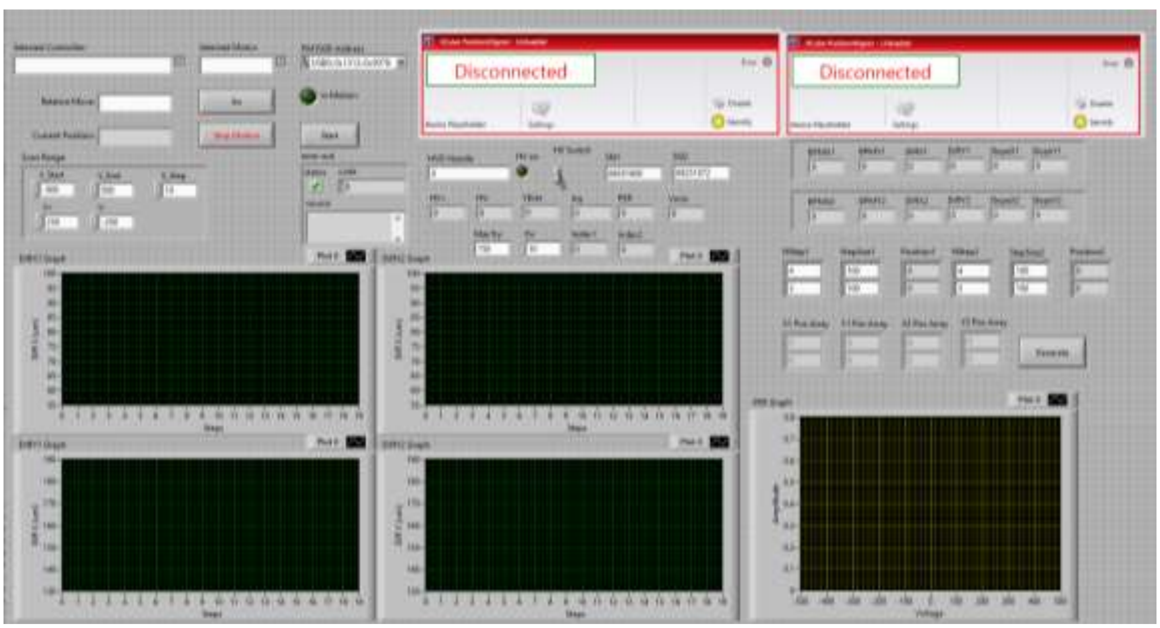

Figure 3: Data Collection Program

The data collection procedure is run with a program, as shown in Figure 3. We can set the range of yaw/pitch angle the data collection program will cover, and we can also set the grid size to determine how precise the scan grid will be. Once being setup, the program will automatically scan through all orientation angles in the range, and do the characterization measurements including intensity asymmetry, beam position difference and polarization extinction ratio. The collected data is written to a SQL database continuously. The whole data collection procedure is described by the Figure 4.

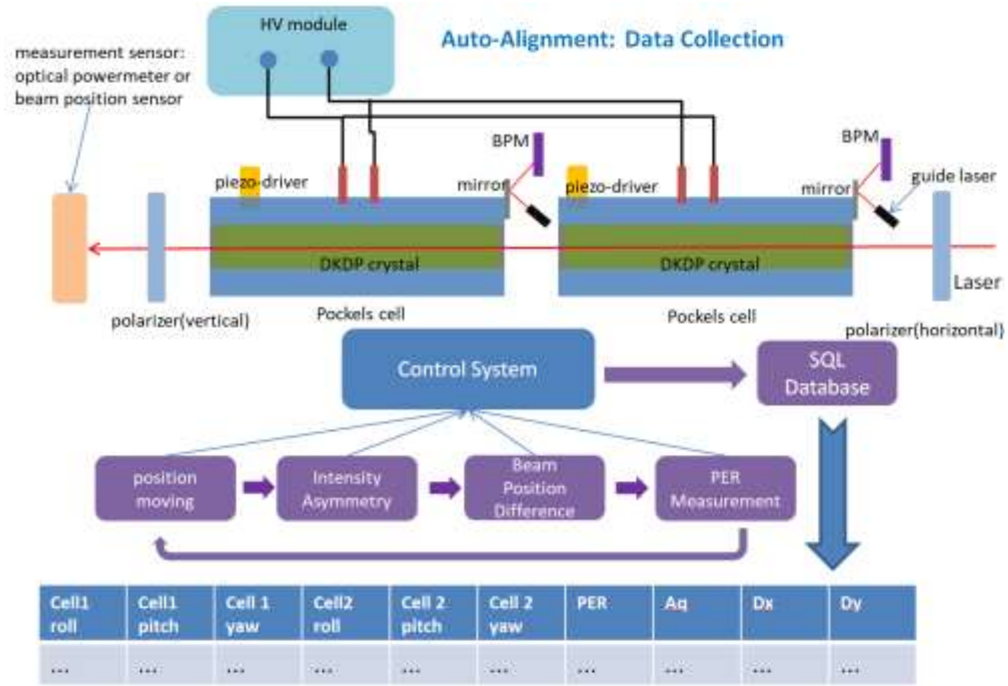

Figure 4: Auto-Alignment data collection procedure: The system uses a guide laser and beam position sensor (BPM) to monitor the position of Pockels cell. The control system commands the piezo-driver to move to desire potion, then do characterize measurement and store data in SQL database, then repeat the loop.

3. BUILD UP NEURAL-NETWORK

As mentioned before, in the dual module Pockels cell system the two cells are independent. During the alignment procedure, we tune each cell's yaw/pitch/roll angles and x/y directions to improve the performance of the system. So there are total 10 parameters that affect the characterization result of the Pockels cell system.

Traditional control systems use parametric models and, in many cases, linear models to model the system behavior. However the relationship between the parameters and Pockels cell characteristics measured in our system is non-linear and difficult to be represented using a parametric model. Neural network (NN) is the state-of-art ML technique and gives the best results in many applications such as computer vision, natural language processing, and speech recognition. The main benefit of modern neural network (or deep learning) against other ML technique is that 1) it does not require assumptions of the underlying model and can model arbitrarily complex and nonlinear relationships; 2) NN does not need feature engineering (the process to extract features useful for ML from raw data) because it can create and select features itself so users can simply feed raw data to a NN model [4].

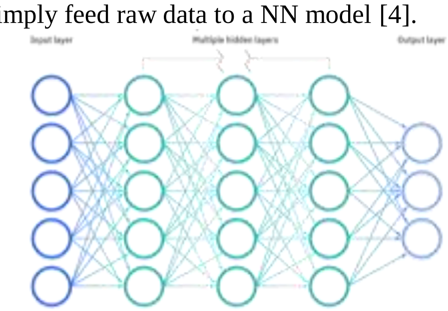

Figure 5: The NN model we build has 3 hidden layers; each has 32, 32, and 16 neurons.

We build the neural network model with Multi-layer Perceptron in scikit-learn package [5]. Figure 6 is an example of the model training. To avoid over-fitting, we use 80% of data to train the model and the rest 20% of data is used to test the performance of the built NN models. And Table 1 shows the accuracy of the built model that has a mean error less than 5% on PER, Dx and Dy prediction on the test dataset.

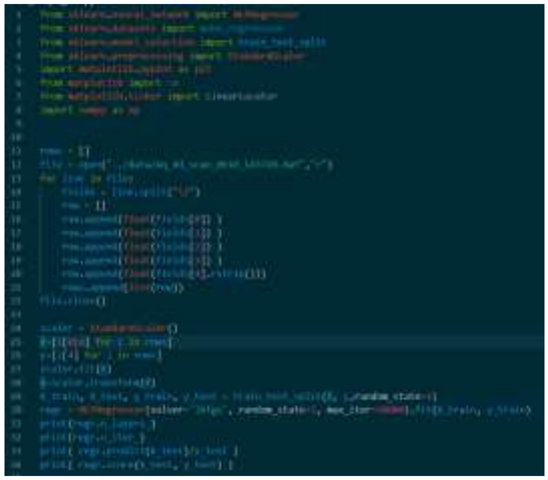

Figure 6: The neural network training script read data from data file then train a neural network which can predict Aq or PER based on cell position.

Model	PER	Aq (Intensity asymmetry)	Dx (beam position difference in x)	Dy (beam position difference in y)
ANN	4.8%	4.1%	3.8%	3.2%

Table 1: Mean error of built neural network

The trained NN model is also plotted in Figure 7 and 8: the Figure 7 shows how the intensity asymmetry changes with yaw/pitch angles; the Figure 8 shows how the PER changes with yaw/pitch angles of the two cells.

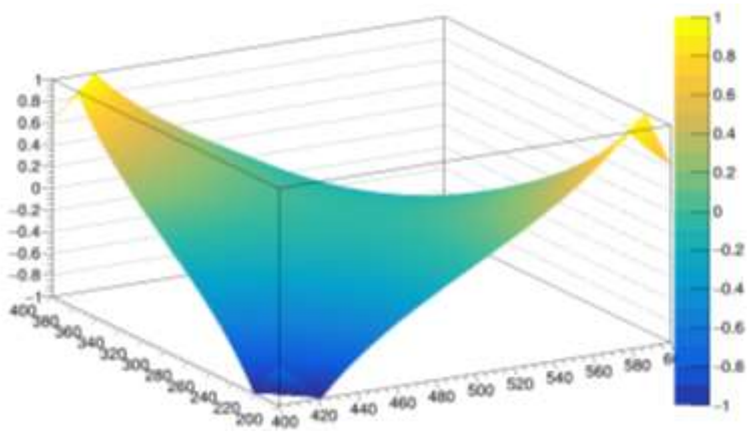

Figure 7: Aq relation with yaw and pitch angles. Here we make the two cells' yaw & pitch angle equal to show it in a 3D plot.

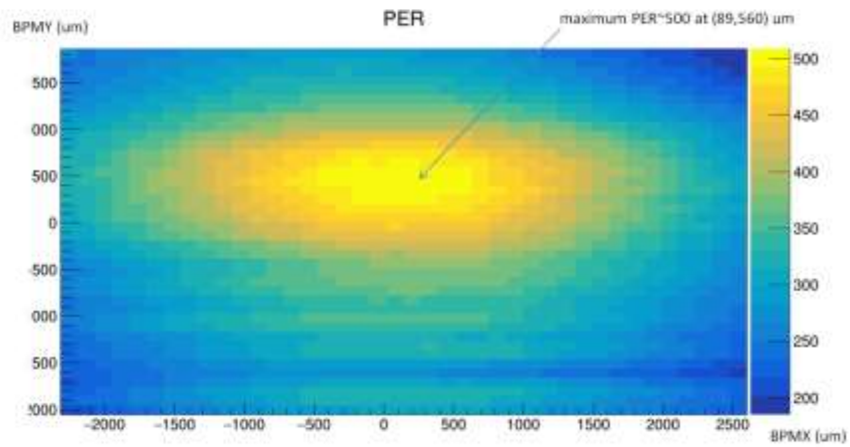

Figure 8: PER dependence on yaw & pitch angles of the Pockels cells.

4. SEARCH FOR OPTIMAL POSITION

In our solution we use NN in two places: 1) to model the dual module Pockels cell system behavior and 2) to find the optimal position (orientation angles) of the Pockels cell. This NN model will be integrated with a gradient-based close-loop control method to find optimal settings of control parameters.

We use a close-loop gradient control integrated with the NN models to find the optimal position for the dual module Pockels cell system. It is certainly possible to use a neural network directly to control the system, or use other optimization methods such as evolutionary algorithms. However, no matter how well a neural network model is trained, real system performance depends on many factors including external factors so predictions given by NN models may not match real system performance and additional tuning is needed. In addition, evolutionary algorithms require a lot of computational resources and are more suitable for offline use rather than online optimization [6].

To test the performance of the auto-alignment system, we start with a state PER = 289, Aq (intensity asymmetry) = 0.134, Dx (beam position diff in x) = 121 um, Dy (beam position diff in y) = 150 um. Then we run the auto-alignment program, after 28 steps we reach the optimal position with PER = 512, Aq = 0.005, Dx = 2 um, Dy = 5 um. The total auto-alignment process takes around 30 min.

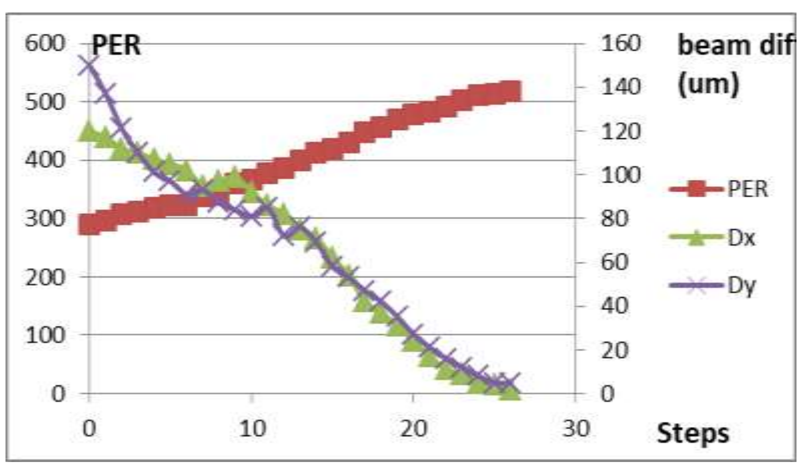

Figure 9: The PER, Dx and Dy changes with steps during the auto-alignment process.

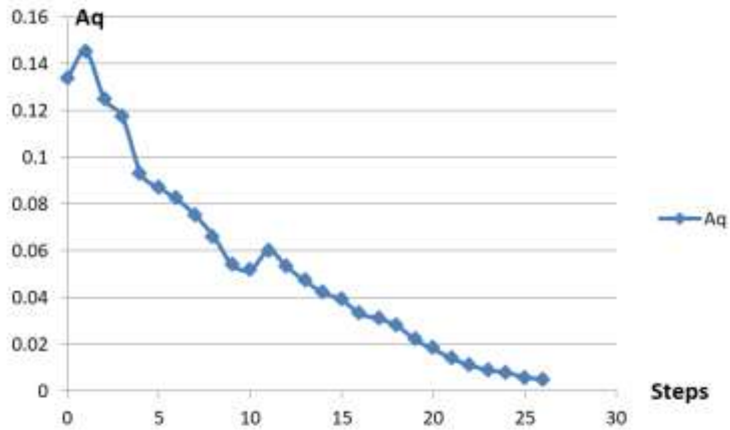

Figure 10: The Aq changes with steps during the auto-alignment process.

5. CONCLUSIONS

In this paper, we combined the machine learning method with the Pockels Cells control system, automatically collected data of Pockels cells optical properties at different orientation angles and physical potions, and built an artificial neural network which can determine the optimal position of Pockels Cells. The trained artificial neural network can predict the PER, intensity asymmetry, beam position difference with a mean agreement around 95%, which makes it possible to find the optimal operation positions of the Pockels cells in a short time. We are working on a follow-on effort to further develop the control system with more control parameters.

6. ACKNOWLEDEMENT

The authors would like to acknowledge the support from Department of Energy under the Small Business Innovation Research Program.

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