ISBN: 978-3-95450-231-8 ISSN: 2673-5490 doi: 10.18429/JACoW-IPAC2023-WEPA109

PARALLEL PREDICTION OF BEAM SPOT WITH NEURAL NETWORKS AND PCA AT TTX*

Shaohong Gu, Wenhui Huang†, Chuangye Song
Accelerator Laboratory, Department of Engineering Physics, Tsinghua University, Beijing, china
Key Laboratory of Particle and Radiation Imaging Tsinghua University, Beijing, china

Abstract

At TTX(Tsinghua Thmoson scattering X-ray source), we try to use machine learning to give the virtual diagnostic of the beam spot. The prediction of beam spot is difficult when the dimensions becomes large. We try to use PCA(Principal Component Analysis) to make it smaller and then use Neural networks to predict it. However, the weight of different dimensions varies widely. We try to predict them parallel and get good results with easy neural networks.

INTRODUCTION

With the development of machine learning, it has been widely used in the field of particle accelerators[1–8]. In this paper, we use machine learning to predict beam spots on TTX[9], it brings certain difficulties due to the large dimension of beam spots[10].

In particle accelerators, there are certain rules in the conventional beam spot distribution, it cannot be distributed arbitrarily on the screen. For example, a regular five-pointed star distribution usually won't appear. In fact, the distribution of beam spot is often elliptical, and the density often has a certain continuity. In short, as long as the distribution of the beam is not completely arbitrary, the information of the beam spot does not need to be represented by the complete number of pixels, dimension reduction can be performed .

Therefore, the prediction of the beam spot does not actually need to predict the brightness of all pixels, we only needs to predict the value of each dimension after dimension reduction, and then apply the inverse algorithm of the dimension reduction algorithm to rebuild the beam spot.

The most commonly used dimension reduction algorithm is PCA[11].

It can get the information of the data with few dimensions and the corresponding weight of each dimension by performing singular value decomposition on the data. It can reduce the dimension and rebuild them very conveniently.

With PCA, a small number of dimensions can contain as much information as possible. the first dimension contains most information, the second dimension contains most part of the remaining information, and so on. Under such a rule, we only need to take the first few dimensions, that is, we can achieve the highest amount of information in the same dimensions, and rebuild the beam spot. This is of great help to the prediction of the beam spot. It help can also be used to predict other information related to the particle accelerators, such as phase space distribution, etc.

THE COMBINATION OF NEURAL NETWORK AND PCA

When the neural network is used for prediction, too many input and output dimensions may lead to a complex network structure, resulting in more neurons, which means that more parameters need to be trained in the neural network. It is more complicated, which means that the difficulty of training is increased, and as the dimensions of beam spot are always too high. It is difficult to achieve perfect prediction if you want to express the parameters of all pixels with a small amount of data in the previous layer, while adding too many neurons means that over-fitting is more likely to occur.

Therefore, we try to reduce the the variables that neural network need to predict by combining the neural network with PCA. The beam spot is first reduced in dimension, and then the neural network only needs to predict few dimensions, which will greatly reduce the complexity of our neural network and reduce the training time. And the small number of dimensions predicted by the neural network can also rebuild the beam spot through the coefficient matrix obtained in the PCA algorithm to rebuild the beam spot.

There are also some problems with this method. Since the amount of information contained in each dimension is different, putting these parameters together is not a good idea as it may leads to imbalance on these dimensions.

Based on this problem, we proposed a parallel training method. After selecting the number of dimensions needed, we train the respective neural network for each dimension separately. Since the output dimension of each network is 1, simple network structures can be used. Then, during the training process, we parallel train several dimensions with the highest residuals. After training for a certain number of epochs, we judge the residuals again and select the dimensions with the highest residuals. Through this method, we are always training several dimensions that are most in need of training, which can greatly improve the training efficiency.

EXPERIMENTAL STUDY

We carried out a simple experimental on the injector of TTX to verify the method. The equipment is shown in Fig. 1, and the relevant parameters and their ranges are shown in Table 1.

An experiment was carried out, we scanned the parameters in the above range and recorded the beam spot. During the process, it's found that when the beam spot is small enough,

* Work supported by National Natural Science Foundation of China (NSFC Grant No. 12035010).
† huangwh@mail.tsinghua.edu.com

ISBN: 978-3-95450-231-8 ISSN: 2673-5490 doi: 10.18429/JACoW-IPAC2023-WEPA109

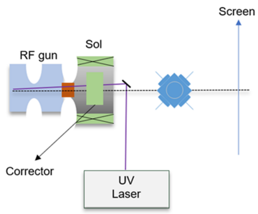


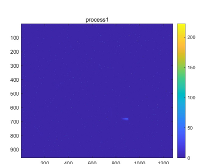
Figure 1: TTX electron gun structure.

Table 1: Prediction Accuracy of the Classification Model

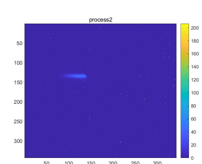
Parameter	Min	Max	Unit
Q	30	150	Pc
soleiod strength	70	120	A
RF gun phase	- 5	5	°
corrector-x	0	0.2	A
corrector-x	0	0.2	A

the brightness of the beam spot will be too high. At this time, the brightness of all pixels within the beam spot range reaches the maximum value, and the internal structure cannot be distinguished. To make it clear, we focused the spot to the best scene, then tune the camera gain down to ensure that this situation would not happen again, and then started the experimental data collection, about 500 sets of data is obtained.

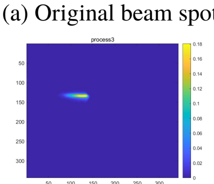
Observing the beam spots we obtained, it's found that these beam spots cannot be used directly, as shown in Fig. 2(a). It can be seen that the proportion of the beam spot in the whole picture is too low, and obvious noise can be observed, so we need to do some thing on it.



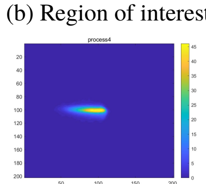
(a) Original beam spot



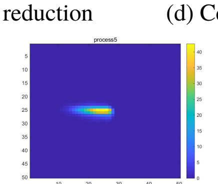
(b) Region of interest



(c) Noise reduction



(d) Centered



(e) Resolution adjustment

Figure 2: Image processing.

Firstly, we try to select the region of interest based on all the beam spots we collected. Since the background of the picture does not change during the experiment, we choose the region with changes in all the beam spot pictures as the region of interest. After that, the initial beam spot becomes to Fig. 2(b).

Then, we started to remove the noise information. We can see that the noise is mainly salt-and-pepper noise. Therefore, we choose to use median filter for image processing[12]. After that, the beam spot becomes to Fig. 2(c).

The noise is removed, and the beam spot distribution becomes clearer, but the beam spot is not in the central area, and different beam spot pictures are distributed in different positions, which is not helpful for PCA. Therefore, we need to move all The beam spot to the central area. Based on the information collected by beam position monitor(BPM) in the experiment, we move the beam spot, and the obtained beam spot is shown in Fig. 2(d). In this way, our model can concentrate to analyze the distribution of beam spots.

At this time, the beam spot is very clear. However, due to the relatively small amount of data, high resolution is not helpful for prediction. Therefore, we appropriately reduce the resolution and adjust it to 50*50. The final beam spot obtained is shown in Fig. 2(e).

After obtaining the beam spot, we perform PCA on them, and the obtained dimension weight is shown in Fig. 3. The dimensions with a weight greater than 0.1% are only the first 15 dimensions, and the sum of their weights is 99.25%. Therefore, we choose to use these 15 dimensions for prediction, and the distribution of these dimensions is shown in Fig. 4.

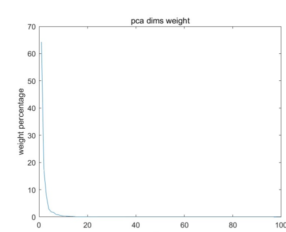


Figure 3: PCA dimension weights.

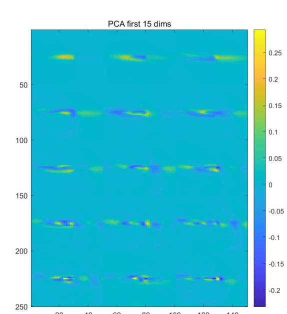


Figure 4: Real beam spot PCA.

ISBN: 978-3-95450-231-8 ISSN: 2673-5490 doi: 10.18429/JACoW-IPAC2023-WEPA109

Next, we verify the ability of the first 15 dimensions of PCA on rebuilding the beam spot, the comparison results are shown in Fig. 5.

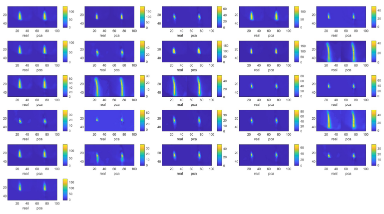


Figure 5: PCA reduction ability.

It can be seen that the 15 dimensions are sufficient to express most information of the beam spot. Then, parallel prediction based on residual error is applied. We set the maximum number of parallelism to 4, and predict the four dimensions with the largest residual error each time.

Due to the relatively small amount of data, in order to prevent from over-fitting, we use a neural network with small size. After optimization, the final neural network structure is obtained, which contains three hidden layers, each layer contains 20 neurons, and the activation function is TANH, the initial learning rate is 0.001, and it decreases by 0.1% every 100 epochs.

After 200 times of parallel training, the accuracy of the validation set does not decrease. The training process is shown in Fig. 6.

Figure 6: Training process.

The predicted results are shown in Fig. 7. Here, we introduce CORR to represent the similarity between the predicted beam spot and the real beam spot. See (1) for its definition. The closer the value is to 1, the higher the image similarity is. In our predictions on the test set, we can see that their CORR values are very high.

$$CORR = \frac{\mathbf{mn}(A_{mn}-\bar{A})(B_{mn}-\bar{B})}{\sqrt{(\mathbf{mn}(A_{mn}-\bar{A})^2)(\mathbf{mn}(B_{mn}-\bar{B})^2)}} \qquad (1)$$

For comparison, we try to directly use the neural network for prediction, choosing the same neural network structure and data segmentation, the obtained test beam spot prediction results are shown in Fig. 8.

The average similarity of the test set of the traditional method is 0.9447, and the minimum similarity is 0.8071. The average similarity of the test set under the new method

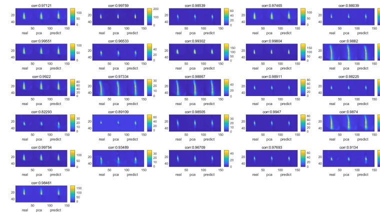


Figure 7: PCA prediction result.

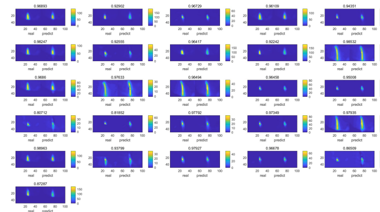


Figure 8: Direct prediction result.

combined with PCA is 0.9728 , and the minimum similarity is 0.8203, which are significantly improved compared to the traditional method. In terms of the number of parameters that need to be trained in the neural network, the traditional one needs to train 53,460 parameters in total, while the new method only needs to train 14,715 parameters. The new method needs to train fewer parameters, while it achieve higher prediction accuracy.

SUMMARY

In this paper, we proposed a PCA-based parallel prediction method for the prediction of high-dimensional parameters such as beam spots. Since the target parameters are not distributed arbitrarily, dimension reduction can be performed, and then only a small number of dimensions are needed to be predicted. The method is applied on experiments data, and good results are obtained. In the experiment, the direct prediction and the prediction method combined with PCA were compared, it was found that fewer parameters is needed to achieve better prediction results with the new method.

REFERENCES

[1] A. Edelen *et al.*, *Opportunities in machine learning for particle accelerators*, 2018.

[2] J. Coello de Portugal and J. Snuverink, "Experience with anomaly detection using ensemble models on streaming data at hipa," *Nucl. Instrum. Methods Phys. Res., Sect. A*, vol. 1020, 2021. `doi:10.1016/j.nima.2021.165900`

[3] J. P. Edelen and C. C. Hall, "Autoencoder based analysis of rf parameters in the fermilab low energy linac," *Information*, vol. 12, no. 6, 2021. `doi:10.3390/info12060238`

[4] E. Fol, R. Tomás, J. Coello de Portugal, and G. Franchetti, "Detection of faulty beam position monitors using unsupervised learning," *Phys. Rev. Accel. Beams*, vol. 23, p. 102 805, 10 2020. `doi:10.1103/PhysRevAccelBeams.23.102805`

ISBN: 978-3-95450-231-8 ISSN: 2673-5490 doi: 10.18429/JACoW-IPAC2023-WEPA109

[5] G. D. Guglielmo *et al.*, "A reconfigurable neural network asic for detector front-end data compression at the hl-lhc," *IEEE Transactions on Nuclear Science*, vol. 68, no. 8, pp. 2179–2186, 2021. doi:10.1109/tns.2021.3087100

[6] B. S. Kronheim, M. P. Kuchera, H. B. Prosper, and A. Karbo, "Bayesian neural networks for fast susy predictions," *Physics Letters B*, vol. 813, 2021. doi:10.1016/j.physletb.2020.136041

[7] S. C. Leemann *et al.*, "Demonstration of machine learning-based model-independent stabilization of source properties in synchrotron light sources," *Phys Rev Lett*, vol. 123, no. 19, p. 194 801, 2019. doi:10.1103/PhysRevLett.123.194801

[8] X. Xu, Y. Zhou, and Y. Leng, "Machine learning based image processing technology application in bunch longitudinal phase information extraction," *Phys. Rev. Accel. Beams*, vol. 23, p. 032 805, 3 2020. doi:10.1103/PhysRevAccelBeams.23.032805

[9] C. X. Tang *et al.*, "Tsinghua thomson scattering x-ray source," *Nucl. Instrum. Methods Phys. Res., Sect. A*, vol. 608, no. 1, S70–S74, 2009. doi:10.1016/j.nima.2009.05.088

[10] P. C. Hammer, "Adaptive control processes: A guided tour (r. bellman)," *SIAM Review*, vol. 4, no. 2, pp. 163–163, 1962. doi:10.1137/1004050

[11] J. Lever, M. Krzywinski, and N. Altman, "Principal component analysis," *Nature Methods*, vol. 14, no. 7, pp. 641–642, 2017. doi:10.1038/nmeth.4346

[12] B. Justusson, "Noise reduction by median filtering," in *Proceedings of the 4th International Joint Conference on Pattern Recognition*, Internat. Assoc. Pattern Recognition, 1978, pp. 502–4.