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# DEEP LEARNING APPLIED FOR MULTI-SLIT IMAGING BASED BEAM SIZE MONITOR*

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*Abstract*

In order to satisfy the requirement of high speed measurement and improve the accuracy of BSM (beam size monitor), multi-slit imaging based BSM has been proposed by SSRF at 2017. However, it is very difficult to deconvolve the image and figure out the beam size, which requires dedicated algorithms to solve this issue. Deep learning is one of the most popular algorithms, which can learn to mimic any distribution of data. In the region of Beam instrumentation, they can be taught to deal with many difficult problem. In this paper, multi-layer neural network is used to process the images from the multi-slit imaging system. Training processes, struct of the neural networks and the result of the experiments will be presented.

## INTRODUCTION

Third-generation synchrotron light sources are aimed to achieve low emittance and a small emittance-coupling ratio. To measure the small beam size in few tens micro meters level is very necessary. Visible light interferometer, developed by T. Mitsuhashi [1] has high resolution in beam size measurement, which has been applied in many syncrotron facilities around the world. However,each method has advantages but also limitations, double-slit synchrotron radiation interferometer is limited at high speed measurement due to its low light throughput. High speed measurement is necessary and important for machine study and operation.

### *Motivation*

In order to satisfy the requirement of high speed measurement and improve the accuracy of BSM (beam size monitor), demo multi-slit imaging system have been designed and tested at SSRF [2]. To figure out the beam size, beam-based calibration method has been employed, by varying the beam size at the source point and observing images of the synchrotron radiation through the 3-slit using a CCD camera, which is effective to find the correlation between the images and the beam size. Nevertheless, beam-based method requires machine study time, which is very valuable for user facilities like SSRF.

Machine learning methods have been widely used in various fields, which is also very popular in the field of accelerator science. Machine learning can use a large amount of historical data to analyze the correlation of physical quantities between different kind of data. It is very useful for image analysis of multi-slit imaging systems. In this paper, multi-layer neural network is used to process the images from the multi-slit imaging based BSM.

### *Deep Learning*

Deep learning (deep structured learning, hierarchical learning or deep machine learning) is a branch of machine learning based on a set of algorithms that attempt to model high-level abstractions in data by using multiple processing layers, with complex structures or otherwise, composed of multiple non-linear transformations. Multi-layer neual network employed in this paper is one of the deep learining algorithm.

This article focuses on the feasibility study of deep learning applied for the analysis of multi-slit imaging. In the following sections, data preparation, struct of the neural networks, training processes and the result of the experiments will be presented.

## DATA PREPARATION

Since this study is only theoretical verification, data used in this paper all obtained from simulation. Synchrotron Radiation Workshop (SRW) code was applied as the simulate tool for the source description and wavefront transport, while algorithm based on python is used to analyse its outputs [3]. SRW is a wave optics simulation code that can take the actual wavefront of the light emitted by a filament like source in the bending magnet and propagete it.

For deep learning, the most important thing is to ensure high quality training data. In this case, the goal is studying the correlation between the image and beam size. Therefore, we need a large number of different source point sizes and combinations of corresponding multi-slit imaging images.

### *3-slit Imaging System Simulation*

First of all, settings of the light source need to be initialized. The parameters of the diagnostic beamline at SSRF are as Table 1. Based on this setting, the beam size is 55.5 $\mu$m at horizontal and 27.7 $\mu$m at vertical. After the design of the source is the optical arrangement of multi-slit based BSM, simulation with SRW is show in Fig. 1.

This is a 3-slit imaging system, parameters of the system: pitch of each slit is 0.7mm, size of slit is 0.5mm and focus length of lens is 0.5 m. For the optical arrangement, the

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Table 1: Parameters of the Diagnostic Beamline at SSRF

| Parameter | Value |
|---|---|
| Magnetic Field | 1.27 T |
| Effective length | 1.5 m |
| Energy | 3.5 Gev |
| Current | 300 mA |
| RMS Energy Spread | 0.001 |
| Horizontal emmitance | 3.9 nm |
| Vertical emmitance | 0.039 nm |
| Horizontal beta | 0.79 m |
| Vertical beta | 20 m |

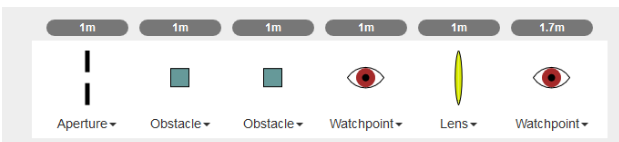


Figure 1: Optical arrangement in multi-slit based BSM simulation.

distance between the 3-slit mask and the source is 1m, the length of lens to source is also 1m, and image to lens is 0.7m. Based on the initial source setting and the desgined imaging system, the image and intensity distribution obtained from 3-slit imaging system is shown as Fig. 2.

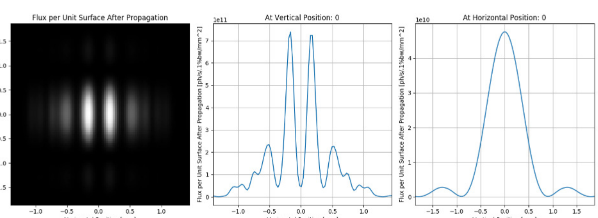


Figure 2: Image and intensity distribution obtained from 3-slit imaging system.

Figure 2 shows that the light intensity at horizontal concentrated in the two main peaks, which contributed to the high SNR (Signal to noise ratio) of 3-slit imaging system.

### *Training Data*

In order to obtain a large number of different source point sizes and combinations of corresponding multi-slit imaging images for training data, parameters of source should be changed. The beam size could be described as Eq.1 [4]

$$S_i^2 = \beta_i \epsilon_i + (\eta_i \sigma_{epsilon})^2 \tag{1}$$

where $S_i$ is the beam size in the horizontal or vertical plane, respectively, (i=x,y), $\beta_i$ and $\epsilon_i$ are the betatron and dispersion functions at the source point and in the corresponding plane; and $\eta_i$ and $\sigma_\epsilon$ are the emittance and the relative energy spread of the electron beam. In this case, $\eta_i$ was varied to obtain different beam size, the beam size at horizontal changed from 55 to 80 $\mu$m, 1680 sets of data were obtained from the simulation for neural network training.

## DEEP LEARNING NERUAL NETWORK

The proposed technique based on deep learning for the multi-slit imaging system is summarized in Fig. 3. This is essentially a supervised regression problem where the input is an image obtained from the imaging sysrem and the label is theoretical beam size, based on this technique, it is expected to be able to obtain the beam size.

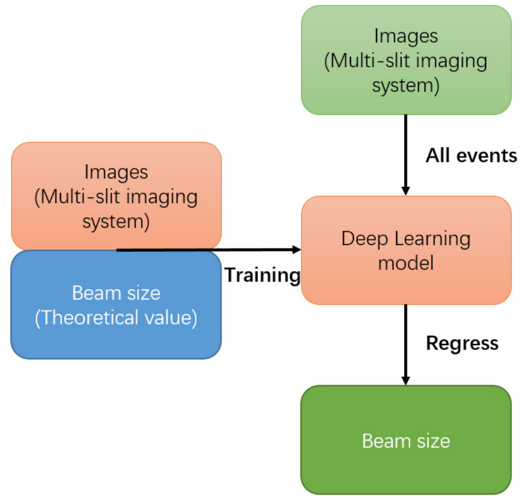


Figure 3: Schematic of the technique based on deep learning for 3-slit imaging system.

### *Nerual Network Design*

The picture size of images obtained from the simulation is 100 pixes * 100 pixes, this case focused on the horizontal, therefore, horizontal projection data was constructed. Under the consideriton of the data validity, 40 pixes at center of the projection data was choosed as AOI. Hence, the input layer of the nerual network(NN) contains 40 nerual units. For the hidden layer, there are two layers, first contains 1021 nerual units, the seconds has 401 neural layers, this is a relatively good parameter configuration found in the neural network training. The output is the beam size. Schematic of the designed NN is shown as Fig. 4.

This is a four layers back propagation nueal network, the neuron activation function selects the sigmoid function, the training function is the traingdx, which updates weight and bias values according to gradient descent momentum and an adaptive learning rate, loss function is mean squred error, which is widely used in regression problem.

A 1680 * 40 matrix was choosed as the input data. In order to enable neural network training results to be well generalized, the input data is divided into training sets, cross-validation sets, and test sets according to a ratio of 6:2:2. In the data preparation process, the beam size is increased in order. The order of the input data has been disrupted to make the training convergence faster and make the neural network more accurate.

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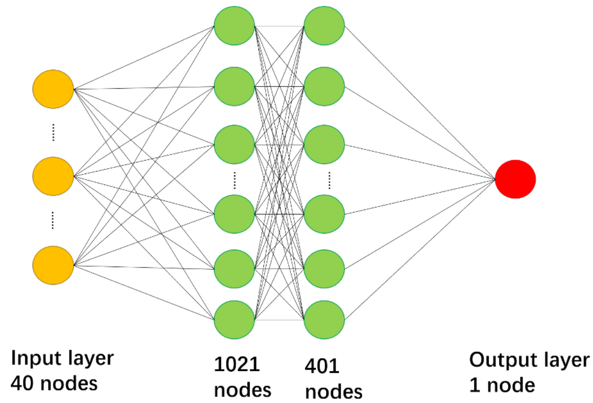


Figure 4: Schematic of the designed neural network.

### *Training Result*

Figure 5 shows the training process, training reached convergence after 9947 iterations, validation performance is 0.0049, training performce is 0.001.

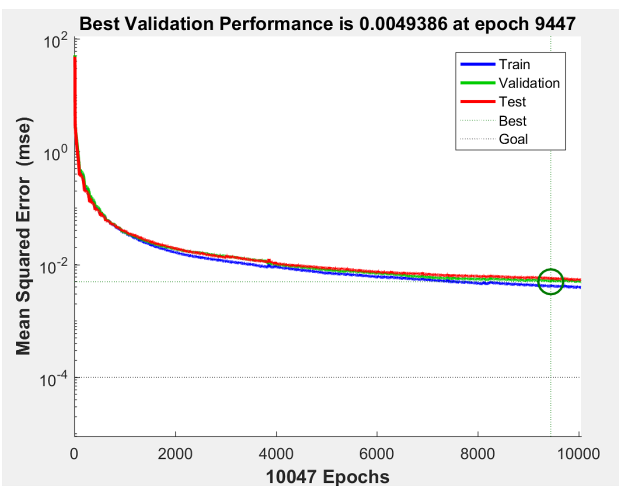


Figure 5: Training process of neural network.

The result of prediction compared with the real data is shown as Fig. 6.

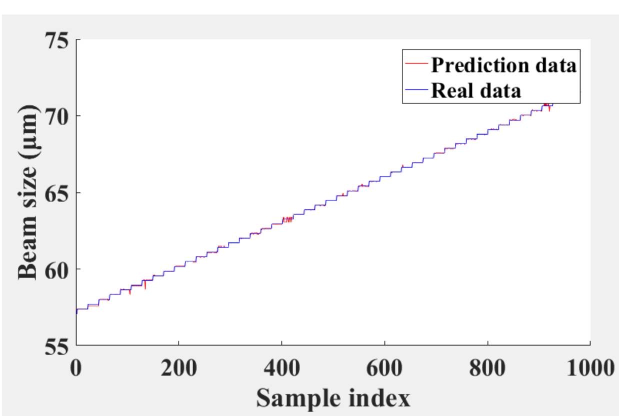


Figure 6: The result of prediction compared with the real data.

The result shows that neural network prediction data agrees well with theoretical data, the residual statistical histogram between the two is shown as Fig. 7. RMS of the residual is 0.045 $\mu$m.

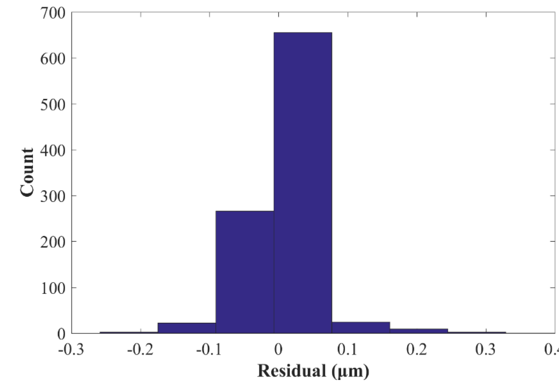


Figure 7: Residual statistical histogram between prediction and real data.

## DISCUSSION

From the comparison between the results of the neural network and the actual theoretical data, while beam size is too large or too small, the prediction accuracy will be lower. Possible reasons come from the following three points:

- The accuracy of the imaging detector is a little bit lower during the simulation;
- Data preparation is still not enough, good network comes from more multiple classes and a larger amount of data;
- Neural networks need further optimization to make the prediction more accuarcy.

Hence, in the next, during the research process, the above three possible causes will be optimized, and the neural network will be further optimized to achieve high resolution.

## CONCLUSION

Multi-layer neural network is used to process the images from the multi-slit imaging system to measure the beam size. Training processes, struct of the neural networks and the result of the experiments has been presented. According to the result, the feasibility of the deep learning method has been verified, the analysis accuracy of the beam size based on the described NN can be achieved to 0.04 $\mu$m. However, it still have a lot of optimization space. In addition, an online training network will be set up in the future.

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