

BEAM INTENSITY PREDICTION USING ECR PLASMA IMAGES AND MACHINE LEARNING

Y. Morita*, RIKEN Nishina Center for Accelerator-Based Science, Saitama, Japan

K. Kamakura, Center for Nuclear Study, the University of Tokyo, Tokyo, Japan

A. Kasagi, Rikkyo University, Tokyo, Japan

T. Nishi, RIKEN Nishina Center for Accelerator-Based Science, Saitama, Japan

N. Oka, National Institute of Information and Communications Technology, Tokyo, Japan

Abstract

Long-term beam stability is crucial for supplying multivalent heavy-ion beams using an electron cyclotron resonance (ECR) ion source. When the beam intensity drops during long-term operation, the ECR ion source parameters must be adjusted to restore the original beam intensity. Continuous measurement of beam intensity using a Faraday cup (FC) while using the beam is impractical. Currently, we estimate the beam intensity during beamtime by monitoring the total drain current, which is an unreliable method. Therefore, we propose a new method for predicting the beam intensity at FC using machine learning. In the proposed method, plasma images captured through a hole in the beam extraction electrode and the operating parameters are considered as input data for training a machine learning model. The proposed method successfully produced rough predictions of beam intensity in short-term validation datasets. This paper presents the prediction model and its prediction results using validation data. The developed model can immediately respond to fluctuations in beam intensity and enable efficient operation of the ECR ion source over extended periods.

INTRODUCTION

In the long-term operation of electron cyclotron resonance (ECR) ion sources, the beam intensity frequently fluctuates during delivery. However, methods such as Faraday cups (FC) cannot be used to diagnose beam intensity during delivery because FC interferes with the beam. Consequently, we have been operating ECR ion sources by inferring changes in beam intensity using the drain current as the leading indicator. Nevertheless, a non-destructive beam intensity measurement method must be developed to automate its long-term operation. Based on the empirical knowledge that operators consider plasma light in the visible light region crucial when tuning ECR ion sources, we devised a method to predict beam intensity from plasma light. In this study, we created and evaluated a model to predict the beam intensity by processing images of visible plasma light obtained through a CCD camera using machine learning. Previous studies have suggested a relationship between plasma light intensity and beam intensity [1]; consequently, this study further aims to predict the absolute value of beam intensity based on this relationship.

* yasuyuki.morita@riken.jp

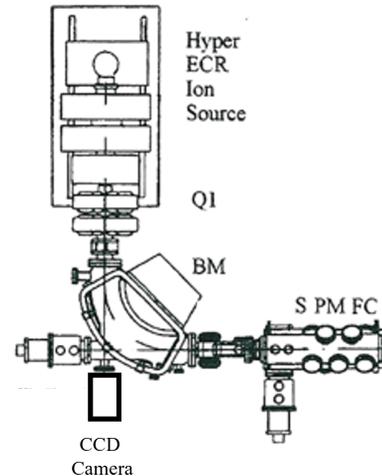


Figure 1: Schematic representation of the LEBT, where beams extracted from the HyperECRIS are focused by quadrupole magnets and then selected for the required charge by bending magnets and slits. The plasma light was captured using a CCD camera through a window in the bending magnet and through an extraction electrode.

EXPERIMENTAL CONDITIONS

HyperECR Ion Source

The 14-GHz ECR ion source “HyperECR Ion Source” (HyperECRIS) [2] at the Center for Nuclear Study, The University of Tokyo, was used to acquire training and validation data for developing the machine learning model. The HyperECRIS can supply gas ion species such as proton, helium, and argon and metal ions such as lithium and iron. In the HyperECRIS, a crucible containing metallic material was attached to a rod tip, and the heat of the plasma was used to vaporize the metallic material to provide metal ions. Therefore, compared to gas ion species, the intensity of the beam tends to fluctuate when metal ion species are supplied. In this experiment, we used a $^{56}\text{Fe}^{15+}$ beam, considering that a more stable gas ion species would not be suitable for evaluating the prediction accuracy, mainly because the fluctuation of the beam intensity is slight.

Parameters

The low energy beam transport (LEBT) from HyperECRIS to FC is shown in Fig. 1. The beam extracted from HyperECRIS is selected through the bending magnets and slits, and the beam intensity was measured at FC. The param-

eters of HyperECRIS and LEBT are summarized in Table 1. For these parameters, EPICS was used, and an acquisition system was established to acquire data simultaneously. The acquisition time was synchronized with the timing of the plasma light imaging described below.

Table 1: Operation Parameters

Controllable parameters	Observable parameters
RF power	Reflection power
Main gas valve	Drain current
Sub gas valve	Plasma light
Main coil current 1	Beam intensity
Main coil current 2	Degree of vacuum
Rod position	
Extraction voltage	
· Slits position (Up, Down, Left, Right)	
Q magnet current	
Einzel electrode voltage	
Bending magnet current	

Plasma Light Image

The novel aspect of this study is the use of plasma light images. As shown in Fig. 1, plasma light images were obtained through the window of the bending magnet at the extraction and plasma electrodes. A CCD camera with sensitivity in this region was used to capture RGB information of the emission in the visible light region. An example of an actual plasma light image during the $^{56}\text{Fe}^{15+}$ beam supply is shown in Fig. 2. Due to the 10 mm diameter of the plasma electrode, the entire ECR zone was not captured. Nevertheless, the star shape of the plasma can be observed. Moreover, the image confirms that the star shape is twisted at the upstream and downstream sides due to the mirror magnetic field.

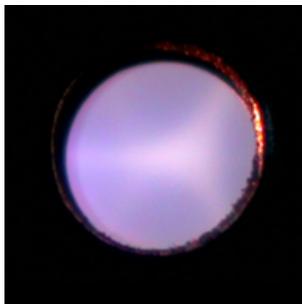


Figure 2: Plasma light obtained through the extraction electrode. The CCD camera captures only the visible light. Although the entire ECR zone is not visible because the diameter of the extraction electrode limits the visible area, the star shape is clearly observed.

MACHINE LEARNING MODEL

Input Data

This study aims to develop a machine learning model to predict beam intensity. As beam intensities are the prediction target, they cannot be used as input data. Thus, plasma

light image and operation parameters other than the beam intensity should be considered as the input data for the machine learning model. In addition to tuneable parameters, other parameters cannot be directly controlled but can be observed, such as the degree of vacuum and RF reflected waves. Other parameters can be tuned but are must be fixed due to the accelerator requirements, such as the extraction voltage and current value of the bending magnet. In this study, all of these parameters were introduced into machine learning without differentiating them using, for example, weighting factors.

Neural Network Model

A machine learning model was developed using a neural network. An overview of the neural network model is shown in Fig. 3. For the plasma light image, ResNet50 [3], a convolutional neural network, was used. The image was cropped to a size of 224×224 pixels to fit the input of ResNet50, and one fully-connected layer after the output layer of ResNet50 was included. The output and operation parameters of the fully-connected layer after ResNet50 were combined with the output of the fully-connected layer after ResNet50. Two more layers of fully-connected layers were used to model the output of the beam intensity values. The output layer is a single continuous number. During training, the mean squared error was used as the loss function.

RESULTS

The performance of machine learning was evaluated using data acquired during the $^{56}\text{Fe}^{15+}$ beam tuning and beam experiments conducted on March 18–19, 2024. After the beam supply ended on March 19, an experiment was conducted to evaluate the effect of changing the current values of main coils 1 and 2 on the $^{56}\text{Fe}^{15+}$ beam. The set of operation parameters and plasma light images obtained simultaneously were used as training data. The training data contained 72619 data points. The validation data were used from the start of the accelerator tuning on March 18 to the end of the beam supply on March 19. A validation dataset was used to verify whether machine learning after training can predict new data. The validation data contained 31646 data points. The beam intensity predictions for the validation data and the beam intensity measured at the FC are shown in Fig. 4. In the validation data, the FC was evacuated most of the time for the accelerator tuning and the beam supply; thus, the beam intensity during that period was not measured, and its value is shown as $0 \mu\text{A}$. The developed machine learning model can predict the beam intensity even when the FC is evacuated and the direct measurement is impossible. Although some errors in absolute values remain, the model reproduces the decreasing timing trend of the beam intensity well. These results suggest that this machine learning model is practical as an indicator of the change of the beam intensity during the beam supply.

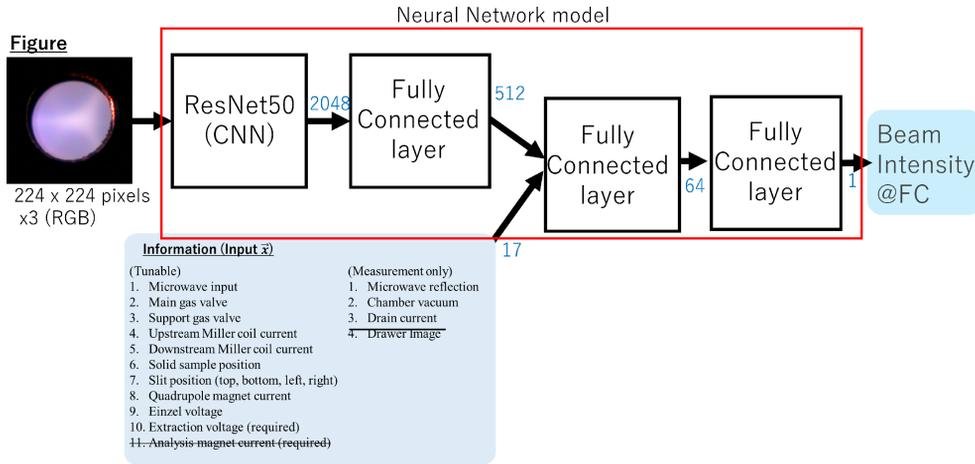


Figure 3: Schematic representation of the machine learning model. Images are input to ResNet50 and then pass through one fully-connected layer. Two additional fully-connected layers are used to predict beam intensity with operating parameters.

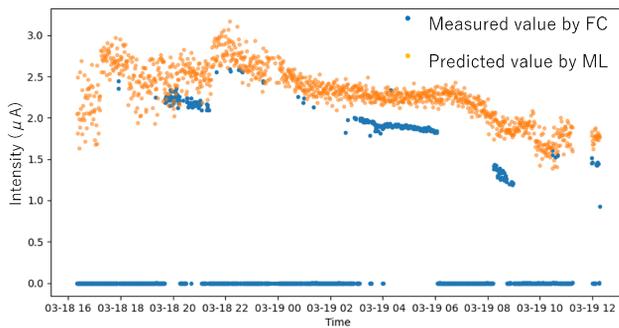


Figure 4: Results of machine learning beam intensity prediction. The model could predict even though the measured values were 0 because the FC were evacuated during accelerator tuning and the beam supply. Although an error in the absolute value remains, the model could predict the beam current without an FC.

CONCLUSION

This study developed a beam intensity prediction method using plasma light images and machine learning for long-term stable control of ECR ion sources. In the proposed method, visible plasma light was captured through the extraction electrodes and used as an input for machine learning

along with operating parameters. Although the method still has some limitations, such as absolute value errors, the results indicate that it performs well enough to identify trends in beam intensity, such as a decrease in beam intensity. The results suggest that predicting changes in beam intensity is possible at any time during the beam supply. This method enables us to respond immediately to changes in beam intensity and operate the ECR ion source more efficiently for long periods.

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