

Unique Origin Unique Future

Reinforcement Learning based RF Control System for Accelerator Mass Spectrometry

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22nd International Conference on Cyclotrons and their Applications, Sep 22-27, Cape Town, Africa

Abstract

Accelerator Mass Spectrometry (AMS) is a powerful method for separating rare isotopes and electrostatic type tandem accelerators have been widely used. At SungKyunKwan University, we are developing AMS that can be used in a small space with higher resolution based on cyclotron. In contrast to the cyclotron used in conventional PET or proton therapy, the cyclotron-based AMS is characterized by high turn number and low dee voltage for high resolution. It is designed to accelerate not one with adding effect of the acceleration of various particles and highed sample amounts. In this work, we proposed an AMS RF control system based controller designed through the modellag near the cyclotron value in response to the environment through the learning process. We have designed a reinforcement learning based controller with RF system as an environment and verified the reinforcement learning based controller with RF system as an environment and verified the reinforcement learning based controller designed through the modelled cavity.

AMS RF control system block diagram



Figure 1 Reinforcement Learning based AMS Control Block Diagram

SYSTEM DESIGN

$$E_{PK} = \kappa_e \sqrt{P_t}$$

electric field from rf source

Here κ_e is coefficient which is determined using computer code and P_t is transmitted power. P_t is changed by cavity coupling coefficient and resonant-frequency mismatch and is related to beam loading effect and reflected power.

$\{P_f, P_r, V_{exr}, V_{bias}\}$

State

 Where Pf is forward power from rf source, Pr is reflected power and Vexr, Vbias is extraction and biases voltage which effect injection beam guality from ion source, respectively.

$$A = \{a/ -\Delta f, 0, \Delta f\}$$

Action

- Where, Δf is the Increment of RF input frequency. Since we use a relatively low frequency

$$R = \{+1, if P_{rt+1} > P_{rt} - 1, if P_{rt+1} \le P_{rt}\}$$

Reward

 Where Pr t+1, Pr t are reflected power at two successive time steps. Agent will get positive reward when reflected power decrease. In other cases, it gets negative reward.

SOFTWARE DEVELOPMENT



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Figure 4 Neural Network weight and biases update process

the input data passes through each layer of the neural network. At this time, the weight and bias values remain at their stored values.

In the update process, the neural network calculates the gradient of the weight and bias according to the input through backpropagation

The weights and biases of neural networks that make up actors and critics are initialized before training. We performed the initialization using a He uniform variance scaling initialize



Figure 5 Actor and Critic Loss function test in traning

 Actor and Critic perform optimization work by using ADAM Optimizer to reduce loss function through training.

Simulation



Figure 6 A2C Resonance Controller Learning Process at 5.8 Mhz Constant Resonance Point



Figure 7. A2C Resonance Controller Learning Process in Resonance Point Shift Model

 Verification of the A2C-based resonant controller was carried out through the forward and reflected power. A2C controller was simulated when the resonance point did not change and also trained by adding a sinusoidal function with an amplitude of 1.5 khz to the resonance point.

Conclusion

A2C based AMS control system design and simulation was performed in this paper. This method is currently being tested with the ion source controller hardware information.



