要約

Improving efficiency and quality on modeling 3D plasma shape in FFHR by introducing Neural Networks

HU KUNQI

Nuclear fusion is a prospective source of energy that is low environmental impact. Various approaches exist for controlled nuclear fusion, with magnetic fields emerging as the most viable means to confine the high-density and high-temperature plasma. This study aims to support the design verification of a magnetic confinement fusion reactor called the Force Free Helical Reactor (FFHR) by constructing a precise three-dimensional (3D) model of the plasma and utilizing 3D visualization techniques, improving the efficiency and accuracy of interference inspection between the internal components of the fusion reactor and the plasma shape.

In chapter 1, the operational principles of the FFHR and the fundamental structure of the plasma within the FFHR are first explained. The chapter then emphasizes the significance of determining the shapes and positions of internal components, such as the blanket and diverter, in the design of the FFHR, considering their interference with the plasma formed inside the reactor. While conventional analysis of the interference between internal components and plasma shape were conducted on 2D cross-sections of the FFHR, the chapter emphasizes the need for an efficient approach to globally overview the 3D shape of the plasma for more accurate and efficient interference inspection. In order to generate a plasma shape 3D model, two closed curved surfaces are employed. One represents the Last Closed Flux Surface (LCFS) and the other represents the envelope of the stochastic area with divertor legs. These surfaces can provide a clear boundary for making it becomes simple to inspect the interference of the plasma and the internal components in the FFHR.

In chapter 2, a basic method for modeling the plasma shape 3D model is explained. For modeling 3D plasma shape, magnetic field lines are obtained through numerical computation. Due to the complex helical magnetic field, magnetic field lines become intricately twisted and intertwined, making it challenging to find a parametric or implicit representation capable of completely describing the structure of all magnetic field lines. To capture the complex plasma shape from magnetic field lines, magnetic field line data is transformed into a scalar field. This involves calculating the distribution of a large number of magnetic field lines for numerous points within the reactor. The scalar value of the scalar field is computed using the distance between magnetic field lines and the points. The Marching Cubes (MC) algorithm is then employed to create isosurface based on these calculations. The modeling takes into account the helical motion of plasma around the magnetic field lines. The radius of this helical motion,

known as Larmor radius, is represented by parallel lines encircling the magnetic field lines. The chapter also presents the evaluation results of the plasma shape 3D model obtained using the proposed method. The experimental results indicate that the quality of the 3D model remains to be improved. The roughness, gaps and margin appeared on the model are expected to be reduced.
In chapter 3, a method to improve the plasma shape 3D model constructed using the basic method from the previous chapter is described. a point cloud data, obtained from the magnetic field lines, where points are labeled with features corresponding to the three plasma areas, the outermost area, the stochastic area and the closed area. This labeled data is used to train a fully-connected neural network (DNN) to predict labels for each point within the reactor. From points with predicted labels, a scalar field is derived under a computation approach different from the one shown in the chapter 2. Instead of calculating the distance from a point to the parallel lines, the relative position of the point to the center of the Larmor radius is considered. The scalar field is then utilized to extract the enveloping surface of the magnetic field lines as isosurface, by using MC method. The experiments demonstrate a significant reduction in the computational time for model construction and an improvement in the 3D model.

Even for the model proposed in the chapter 3, there remain a problem arisen from the insufficient number of magnetic field lines consisting divertor leg parts of the stochastic area in the original data. In chapter 4, a method for predicting the starting points of magnetic field line tracing using feature analysis of magnetic field line data and convolutional neural network (CNN) is explained. The approach involves analyzing the magnetic field line data presented in the chapter 2 to identify suitable starting points for tracing magnetic field lines which belongs to the divertor leg parts in the fusion reactor. An approximation algorithm is presented which enables us to obtain the position of starting points. For now, the FFHR is still in the experimental design phase, and its specification undergo frequent revisions. It is time-consuming to find suitable starting points for tracing magnetic field lines every time when the specification of FFHR is changed. Main specification factors of FFHR include the magnitude of current passing through the coils inside it, altering the magnetic field intensity distribution. To overcome this problem, a prediction method based on CNN, specifically the Visual Geometry Group (VGG), is presented. The proposed CNN model takes an image representing the magnetic field intensity distribution for a given FFHR specification and outputs parameters for computing suitable starting points. Training data for the model has been collected using the proposed approximation algorithm. Experimental results indicate that the proposed method enables us to efficiently find the starting points for tracing magnetic field lines consisting divertor leg parts in a short time.

In chapter 5, a method for visually checking the interference between the internal components of the fusion reactor and the plasma shape in 3D space is explained. Initially, the shortcomings of the interference check feature using conventional Computer-Aided Design (CAD) software are pointed out. Subsequently, the chapter introduces methods based either on texture mapping or volume rendering to visualize the state of interference. In texture mapping method, probability for the vertices in the FFHR model is computed by the method presented in the

chapter 3. Texture mapping is then performed based on the probabilities. In volume rendering method, a conversion from mesh data to volume data is conducted on the FFHR model. The probability of the scalar field representing plasma shape and volume data of the FFHR model are summed, forming a new volume data for rendering. The effectiveness of interference checks using these visualization techniques is discussed through experiments.
In chapter 6, a summary of the overall achievements of the paper is presented, and the future research directions are briefly outlined.

This study contributes to the design verification of the FFHR. As far as being investigated, this study is the first to apply deep learning to the construction of plasma shape 3D models. It provides valuable experience for the application of deep learning in a segment of the fusion field. At the time of writing this dissertation, we observe an increasing trend in the application of deep learning techniques in fusion research. As future research directions, close relationships are to be established with other researchers involving deep learning techniques in the field of fusion reactor design. Moreover, there is a focus on refining a user interface for interference inspection under the feedback from the National Institute for Fusion Science, accelerating the practical applications of nuclear fusion in real-world scenarios.