Estimation of L-H transition time by statistical methods on HL-2A

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1. Introduction

Controlled fusion is very promising energy for mankind in the future, and one of the important issues on Tokamak fusion is to understand the physics of low-confinement to high-confinement mode transition (L-H transition). To analyze the complex physics and determine the exact time when the event occurs is a difficult problem. Meanwhile, real-time control has assumed an increasingly important role in Tokamak experiment, and the time at which the plasma reaches another important confinement state (e.g. from L to H mode) should be available in the feedback loop for the better controlling. But until now, the L-H transition time on HL-2A Tokamak is still estimated by relating multiple signals of the discharge in a manual way. Obviously, this procedure is not optimal at all, because there is very large amount of data stored in fusion database, and it also can not be used for real time control. Therefore, the development of a technique for the automatic estimation of the time instant associated with the occurrence of H mode is an urgent need.

On-line identification of confinement regimes was first achieved on ASDEX Upgrade Tokamak. Since then, several kinds of method has been used to identify the confinement regimes, such as fuzzy logic, classification trees [1], MLP neural network [2], support vector machine (SVM), and Bayesian statistics [3]. SVM and Bayesian theory are known to be very powerful techniques for the classifier development. Both of them are based on statistics, and from the results of JET, they could perform very well. On HL-2A, these two statistical methods are also used to identify the L-H transition time.

2. Using SVM and Baysian classifiers to identify the transition time

The "H-mode" was firstly achieved on ASDEX [4]. Once the plasma reaches in H-mode confinement region, it will produce more energy from nuclear fusion. The H-mode plasma often induces a kind of MHD instability, called edge localized mode (ELM), manifesting as bursts in the H_α (D_α) emission. On HL-2A, the most

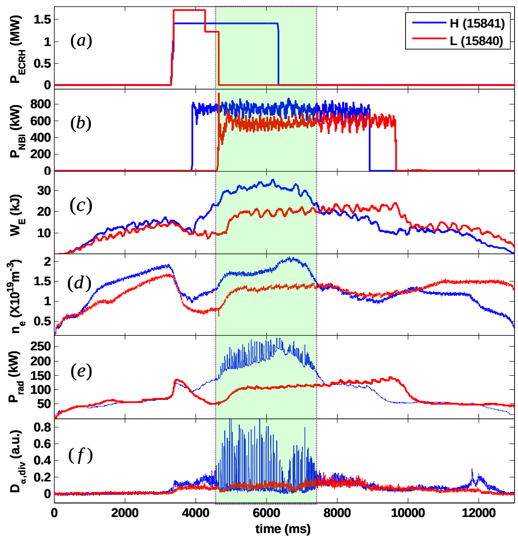

Fig. 1 The differences between the H-mode (15841) and the L-mode (15840).

common H-mode is ELMy H-mode [5]. Figure 1 shows the temporal evolution of the parameters in the H-mode discharge in contrast with those in the L-mode discharge. Around 460 ms in shot 15841, the H-mode appeared with typical ELMs. The plasma stored energy increased gradually around the transition.

About 100 H-mode discharges on HL-2A has been chosen for this estimation. And among them, 209 L-mode moment data and 233 H-mode data is selected to develop the classifier. At each discharge, there are lots of signals saved in the database. Considering the expression of the threshold of L-H transition, only a few important signals were selected. They are: line-averaged electron density n_e, stored energy of the plasma W_E, its radiated power P_{rad}, toroidal magnetic field B_t, plasma current I_p, and the total heating power P_{tot}. Therefore, the data space is six–dimensions ($\mathbf{x} = [n_e, W_E, P_{\mathrm{rad}}, B_t, I_p, P_{tot}]$). The number of the signals should be suitable. If it is too small, the classifiers can not tell the L and H mode data with a high accuracy. While if it is too large, the classifiers would be complicated, it would spend longer time to calculate, which is not good for application in the on line situation. 80% data is randomly selected as train data set, used to develop the classifiers, while the left 20% data is used as test data set to make sure the classifiers are good enough. All the data points are labeled by y; y equals 1 means the data point is L-mode data; and equals 2 means it is H-mode data.

Support Vector Machine (SVM) is a supervised algorithm developed by Vapnik[6]. It tries to develop an optimal separating hyper-plane, which can divide the two group data very well. In the low dimension space, sometimes it is not possible to find the plane. Under this condition, it maps the data points into a high dimensional feature space, using the kernel functions. In the high dimensional space, the linear plane could be found to separate the data points.

In SVM method, the optimal separating hyper-plane is found from training the train data set. In order to obtain a good model, the parameters (penalty coefficient and slack variables) should be chosen carefully. And the predict accuracy of the test set is between 91.3043% (84/92) and 96.7391% (89/92). There may be different among each test, because the train set and the test set are randomly selected. Form the test results, it could be certified that the SVM learning machine works well. And it can classify L-mode and H-mode data points. If the data is arranged in time order, just like the state of the plasma evolution with time, SVM could find when H mode occurs. Figure 2(a) shows about the shot 11335, SVM identify the transition time is at 738 ms. And the result agrees well with the deuterium emission signal (D_α). Now, Although SVM can tell the transition time, the detail of the transition can not be shown. The probability of H mode is calculated by the expression $P_H = 1 - 1/\{1 + \exp[-kD(\mathbf{x})]\}$, $D(\mathbf{x})$ is the distance between the data point and the optimal separating hyper-plane, the parameter k is assigned. Figure 2(b) is one example of the H-mode probabilities during the L-H transition.

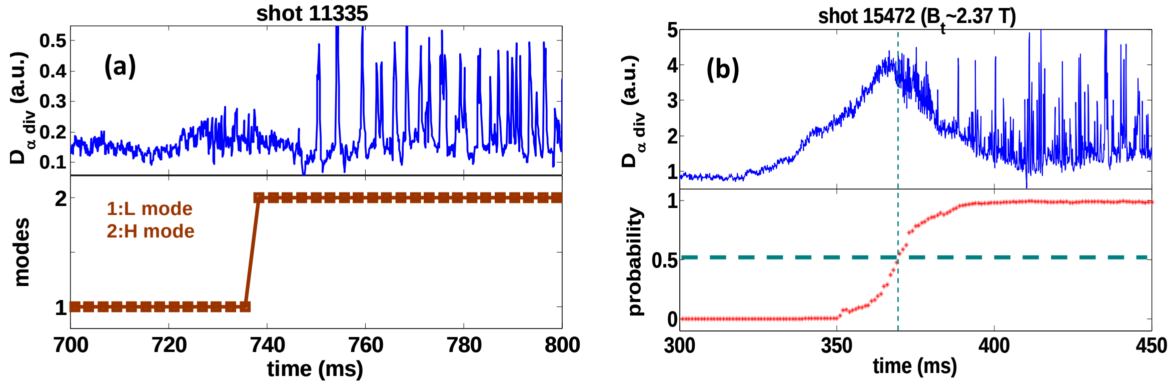

Fig. 2 Estimation of L-H transition time by SVM. (a) directly using SVM; (b) probabilities of H-mode during the transition event

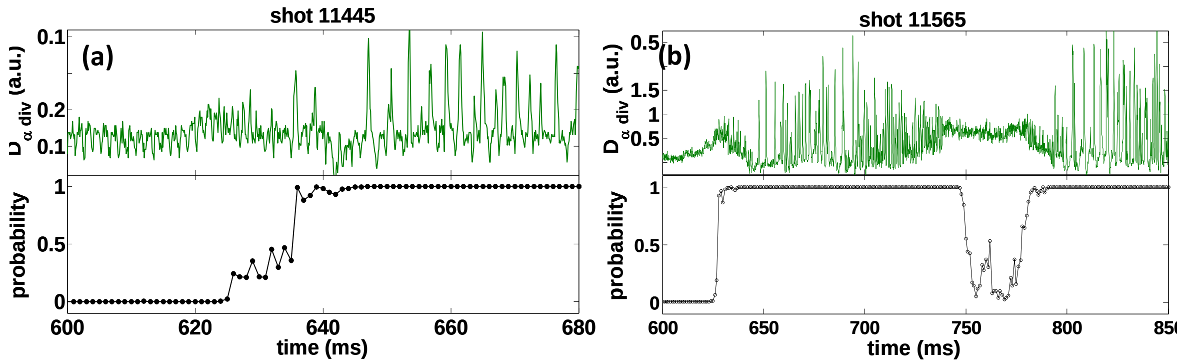

Fig. 3 Two examples of the L-H transition time, estimated by Bayesian classifier

Bayesian classifier is a simple probabilistic classifier, based on the independence assumption of Bayes' theorem. In this method, Parzen window method is used to calculate the conditional probabilities, and it is assumed the prior probabilities of the unspecified data belonging to L-mode or H-mode are both 50%. Using Bayes' theory, and comparing the two probabilities (L and H), can figure out the data is in L-mode or H- mode. Similarly, it could identify the L-H transition time by classing the data, which is in time order. And figure 3 is two examples.

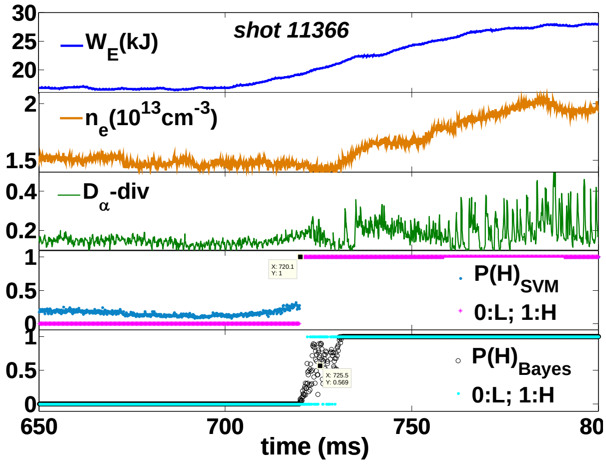

Fig. 4 Comparison of the two statistical methods.

From the discussion above, both of the two statistical methods can estimate the L-H transition time. Figure 4 shows the estimate results of the two methods in one H-mode discharge on HL-2A. Bayesian classifier often works better than SVM. There may be something should be improve in SVM method. Because it is more complicated, some parameters in this method may have more suitable values.

3. Summary

There are hundreds of H-mode discharges in the HL-2A database since the first H-mode discharge of shot 11329 in 2009. In order to test this method, some of the discharges are chosen as the tests. Most of the data can be well estimated by SVM and Bayesian classifiers. The accuracy of estimated time is about within 10ms, compared with that judged by the manual method.

There are still some aspects could be improved. First of all, the chosen parameters should be considered more carefully. Until now, the H-mode discharge in HL-2A is almost around two toroidal magnetic field values (1.33T and 2.35T, respectively). So in this situation, this parameter may not very important in the component of the $\mathbf{x}$. And the other signals may be selected, for example, the toroidal voltage of the plasma, and some parameters of the edge plasma, because the plasma edge condition is very different from L-mode to H-mode. Secondly, the time instant at which the data is selected should be close to the transition time. There is the hysteresis in the threshold power between L-H and H-L transitions. The input power P_{tot} is larger in L-H transition than that during the H-mode. So the time instant may be chosen at the near sides of the transition. Thirdly, the value of the parameters in the SVM classifier should be chosen more carefully to develop a better SVM classifier.

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