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Novelty Detection for On-Line Disruption Prediction Systems

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ABSTRACT

One of the main factors limiting the implementation of neural networks in industrial applications is the difficulty of detecting potentially unreliable outputs. This could be the case of the neural disruption predictor installed in JET, where new plasma configurations might present features completely different from the ones observed in the experiments used in the training set. This 'novelty' can lead to incorrect behaviour of the network. A Novelty Detection method, which determines the novelty of the output of the neural network, can be used to assess the network reliability. In this paper, two approaches to Novelty Detection are tested, i.e., Self Organising Maps and Support Vector Machines. Preliminary results are encouraging, in particular when referring to false alarms.

1. INTRODUCTION

Disruptions are one of the major issues in current nuclear fusion tokamak research. Recently, the disruption predicting capability of Neural Networks was stressed in [1-3]. It was also shown that diagnostic signals could be used to provide an impending neural disruption warning indicator. The drawback of this approach is that the trained network could deteriorate its performance once it is on-line. In fact, a network that is trained to discriminate between inputs coming from a set of distributions will be completely confused when input data comes from an entirely new distribution. This could be the case in the JET, where new plasma configurations can lead to unknown discharges. An improvement can be made using *Novelty Detection* techniques [4]. Recently, Novelty Detection methods have been proposed in the literature to determine the degree of novelty of a given input based both on statistical and neural network approaches [5, 6]. In this paper, two neural approaches (Self Organising Maps and Support Vector Machines) are used to determine the novelty of the output of the neural disruption predictor [2]. In the on-line application, the Novelty Detection should be used to assess the reliability of the network output, i.e.,

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[*] See the Appendix of J.Pamela et al., Fusion Energy 2004 (Proc. 20th Int. Conf. Vilamoura, 2004) IAEA, Vienna (2004)

samples having a low confidence have to be discarded and used off line to update the disruption predictor.

2. THE NEURAL PREDICTION SYSTEM

The predictive system structure consists of some blocks mutually connected: a clustering block, a novelty detector, and a Multi Layer Perceptron (MLP) neural network (see Fig. 1). During the system training, a Self Organising Map (SOM) performs a clustering procedure, a traditional MLP is trained to give an alarm in case of impending disruption, and a Novelty Detector (ND) is built with the same input data used for the MLP developed in [2]. For each disrupted pulse, one SOM is fed with the values of 9 suitably chosen diagnostic signals [2], sampled at each time instant. The SOM is used to identify the precursor phase, i.e., to discriminate between 'safe' samples and samples containing information about the disruption proximity. Moreover, the SOM is used for data reduction, i.e., only one safe sample for each cluster is selected for the training of the MLP and of the ND. During the

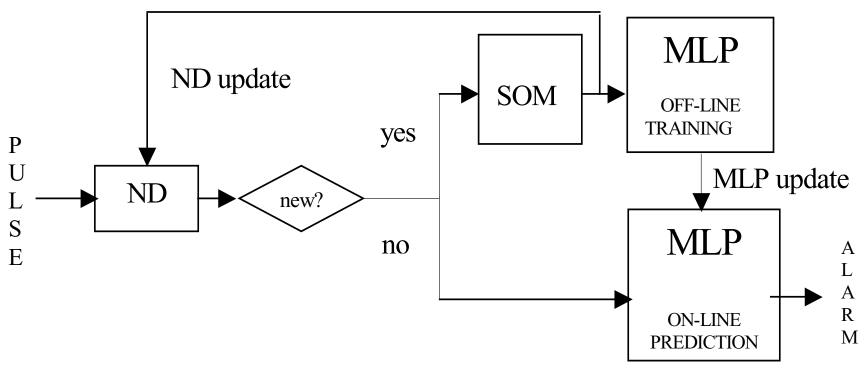

Figure 1 Disruption prediction scheme – on line application

on-line application, the ND is fed with all the samples of the pulse. The ND is used to assess the reliability of the MLP output, i.e., new samples having a low confidence ('new' samples in Fig. 1) have to be discarded and used to update the disruption predictor.

3. NOVELTY DETECTION TECHNIQUES

Several methodologies for Novelty Detection have been recently developed [4-6]. There is not a single best model and their success mainly depends on the statistical properties of data handled [5]. In this work, two neural approaches have been carried out, based on SOMs and Support Vector Machines (SVMs).

In the case of SOMs, each neuron of the map is represented by a prototype vector. For each input, the output vector is composed by the values of the distances between each prototype and the input sample. The Best Matching Unit (BMU) is the nearest neuron in Euclidian meaning. Samples significantly different from those present in the training data have a distance from the BMU greater than that relative to the samples in the training set. Therefore, a threshold can be placed on the ratio of this distance to the maximum distance on the training set [6]. The second approach is based on SVMs. In the simplest case, the support vectors are used to generate a minimum volume hyper-sphere that encompasses almost all the data used in the training set. The radius of the sphere is obtained from trade-off between the volume of the hyper-sphere and the number of target points outside the sphere. A test point is labelled as new if the distance to the centre of the sphere is greater than the radius. In order to address the problem of non-spherically distributed data different kernels can be used, e.g. radial basis functions [6].

4. RESULTS

The SOMs have been trained by means of the SOM Toolbox for Matlab, realised by the Helsinki University. A threshold has been defined for each neuron, equal to the maximum value of the distance from the prototype for each training sample associated to the neuron. When the SOM is used as the Novelty Detector, a sample is labelled as novel if the distance from the BMU is greater than the corresponding threshold. The non-linear SVM has been trained for novelty detection [7] using the OSU SVM Classifier Toolbox for Matlab, based on the version 2.33 of the software library LIBSVM. The kernel is a radial basis function. In both cases the results have been evaluated considering how the detection of novel inputs affects the on-line application of the neural predictor. Table I reports the performance of the MLP [2], and the performances of the proposed system using SOM as ND, and using SVM as ND, in terms of Missed Alarms (MAs) and False Alarms (FAs), for the test set composed by 86 disrupted pulses and 188 safe pulses. These performances have been calculated discarding the pulses labelled as novel by the NDs.

	MLP Test Set	MLP+SOM Test Set	MLP+SVM Test Set
MA	32.5%	30.0%	30.9%
FA	5.8%	1.7%	4.8%

Table I. System Performance

More precisely, 8 of the 11 FAs predicted by the MLP are reported as novel by the SOM ND, thus the number of FAs in the on-line application decreases. Moreover, 13 of the 28 MAs predicted by the MLP are reported as novel by the SOM ND. This result does not affect the on-line application, rather improving the understanding of the data and explaining some of the MLP results. Unfortunately, 23 disrupted pulses, correctly predicted by the MLP, were reported as novel by the SOM. Although the number of FAs and of MAs decreases, the discrimination capability of the system in the on-line application reduces. The most severe requirements however concerns the FAs. In experimental machines such as JET, it is important to allow the complete exploration of the scientific parameters which the occurrence of FAs might hinder. The SVM reports as novel 2 of the 11 FAs predicted by the MLP, while it reports as novel 3 of the 28 MAs. Moreover, the SVM reports as novel 2 of the 58 disrupted pulses correctly predicted by the MLP.

5. CONCLUSIONS

The unavoidable ageing of a neural prediction system is an important problem for the experimental machines, as JET, where new states of the plasma are explored. So, it is crucial to have a system able to measure the reliability of the network output and to automatically update the network in the case of plasma configurations not used during the training phase. In particular, the proposed Novelty Detection techniques appear promising for enhancing predictor reliability and useful in reducing false alarms during the on-line operation.

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