The migration of a Neural Network Observer training using the Deep Learning approach

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Abstract. This paper presents the training of a Neural Network Observer using the Deep Learning approach. Then, we suggest a brief comparison between the use of a classic neural observer supervised by the back-propagation algorithm with a Matlab simulation and a new neural observer used the Deep Learning with a Keras, Tensor flow simulation applied to the same example. Deep learning and neural networks may be an intimidating concept, but since it is increasingly popular these days, this topic is most definitely worth your attention. Fortunately, we have deep learning methods by which we can surely circumvent these challenges regarding feature extraction. This study explains the necessity to improve the way of learning for estimation purposes and upgrade the performance of this kind Observer so its migration. According to the results, we propose the migration of the Neural Network Observer for a nonlinear system, which is well trained.

Introduction

Neural networks are increasingly studied in the research due to their ability to predict complex problems and their learning mechanisms based on parallel processing of information. Various architectures and learning techniques have been proposed and discussed in order to solve several problems. Our motivation is to combine two axes of research, which differ totally in term of applications, and to be up to date with the IA, Machine Learning and the Deep Learning as new knowledge. In this section, we present the multilayer networks training algorithms for the neural observer in two cases [2]. The first case refers to a classic Neural Observer and corrects its weights based on the back-propagation algorithm or an Hybrid approach [4].
The second case is based on the new technic of Deep Learning [1] applied to the non-linear observer [3] in order to compare their responses and improve the estimation error for example.

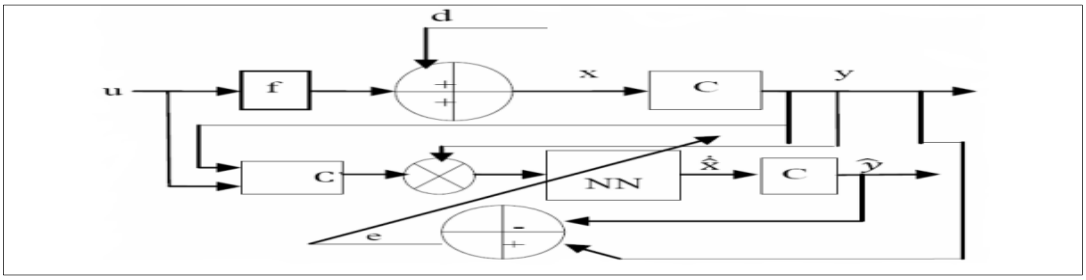

Figure 1: The structure of Neural Observer [2]

Furthermore, the performances of the proposed Neural Observer are tested on a physical nonlinear system. The neural observer assesses the state of the system despite the fact that the nonlinear dynamics of the system is assumed a priori unknown. The comparison will be also between the Matlab language and the Keras as our Python Deep Learning. In addition, we will compare also the efficacity of the two Learning algorithms of the Neural Observer according to their attitudes in estimation purposes.

Results and Discussion

We have trained the proposed Neural Observer tested on a physical nonlinear system named two tanks in cascade which is presented in figure 2; It's is composed of a set of elementary components. Various sensors allow us to measure the height of the product in the tank top (h1) and the tank bottom (h2) and the rate of entry of the product (qe1) and (qe2) in the tank top and the pan low respectively [2]. Using the Library Keras added to Python Language, we find that this nonlinear system has different estimation errors for the Neural Observer which has been already decreased and has small value nearly to zero. The rapidity of our algorithm is also detected comparing to the previous simulation. The Deep Lerning approch has already improved the performances of our Observer.

References

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