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Constructive multi-output extreme learning machine with application to large tanker motion dynamics identification

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ABSTRACT

In this paper, a novel constructive multi-output extreme learning machine (CM-ELM) is proposed to deal with a large tanker motion dynamics identification. The significant contributions are as follows. (1) Driven by generated tanker dynamics data from the reference model, the CM-ELM method is proposed to identify multi-output dynamic models. (2) The candidate pool for CM-ELM is randomly generated by the ELM strategy, and ranked chunk-by-chunk based on a novel improved multi-response sparse regression (I-MRSR) incorporated with λ weighting. (3) Consequently, the constructive model selection works with fast speed due to chunk-type training process, which also benefits stable hidden node selection and corresponding generalization. (4) Furthermore, output weight update on the final CM-ELM model randomly selected from the elite subset is conducted to enhance the overall performance of the resulting CM-ELM scheme. Finally, the convincing performance of the complete CM-ELM paradigm is verified by simulation studies on not only tanker motion dynamics identification but also benchmark multi-output regressions. Comprehensive comparisons of the CM-ELM with ELM and OP-ELM indicate the remarkable superiority in terms of generalization capability and stable compact structure. Conclusions are steadily drawn that the CM-ELM method is feasibly effective for tanker motion dynamics identification and multi-output regressions.

1. Introduction

On the one hand, the promising extreme learning machine (ELM) method for single-hidden layer feedforward networks (SLFNs) has attracted comprehensive and intensive research since Huang et al. [1] proposed the seminal work. The main idea of ELM strategy is intuitively realized as follows. Hidden nodes are randomly generated and output weights are analytically determined by pseudo-inverse technologies. It is evident that the ELM is an extremely fast batch learning algorithm and can provide good generalization performance [2]. As a consequence, the ELM does not need any iterations to determine the hidden node parameters, and dramatically reduces the computational time for training process. Actually, the randomness and diversity of hidden nodes should be guaranteed for high generalization performance. In this case, the determination for the suitable or optimal number of randomly generated hidden nodes becomes an interesting and critical issue to elaborate the ELM advantages. However, the original ELM [3] does not provide any effective solution for architectural design of the network. In most cases, the suitable number of hidden nodes is pre-defined by a trial and error method, which may be tedious in some applications.

In order to circumvent the above-mentioned problems, some improvements to the ELM for optimal structure have been proposed in two heuristic approaches, i.e., destructive and constructive methods, which have been effectively implemented in fuzzy neural networks [4–6]. For the former approach, Rong et al. [7] have presented a pruned ELM (P-ELM), for classification problems, which starts with a large network and then eliminates the hidden nodes having low relevance to the output. Miche et al. [8] have proposed an optimally pruned ELM (OP-ELM) by using the multi-response sparse regression (MRSR) algorithm [9] and leave-one-out (LOO) validation for pruning strategy. Evidently, these methods within destructive paradigms would face common difficulties that the algorithm starts with a large scale structure which inevitably increase the computational burden. For the latter approach, the incremental extreme learning machine (I-ELM) [2] and its variants [10,11] proposed by Huang et al. are proposed to add hidden nodes one-by-one to the hidden layer and incrementally update output weights. However, those algorithms cannot lead to an optimal network structure automatically, and hidden

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nodes are added to the SLFN merely in one-by-one manner. Feng et al. [12] have proposed the error minimized extreme learning machine (EM-ELM), which can add random hidden nodes one-by-one or group-by-group. Unfortunately, the nodes added into the hidden layer are randomly generated and might deteriorate the performance with increasing hidden nodes since no generalization measure is guaranteed. Nevertheless, the resultant network structure would be much similar to original ELM if high prediction performance is required. A constructive hidden nodes selection of extreme learning machine termed as CS-ELM is proposed by Lan et al. [13], whereby the hidden nodes are selected by the MRSR and unbiased risk estimation based criterion C_p. However, the CS-ELM works for single-output regression and the hidden node selection conducts in one-by-one manner.

On the other hand, as the potential application in this paper, the large tanker maneuvering dynamics play a fundamental role in the whole guidance, navigation and control (GNC) system. Focusing on this essential issue, many researchers have proposed varieties of vessel motion models, mainly including Abkowitz model, MMG model and response model [14]. These three types of models preserve distinct features as follows. Abkowitz model pursues accurate hydrodynamic derivatives at the cost of clear presentation for variables, and therefore results in difficulties for control system design. To the contrary, MMG model and response model focus on analysis and synthesis of model based control systems while the model accuracy would be lower since MMG and response models could be considered as simplifications of the Abkowitz model to some extent.

Within the previous model frameworks of vessel motion, studies on system identification for hydrodynamic derivatives and input–output nonlinearities have been conducted by using various methods, i.e., simplified linearization [15], estimation-before-modeling technique [16], and support vector regression method [17], *etc*. However, the resultant overall mathematical formulation of vessel maneuvering is usually complicated due to the existence of hydrodynamic nonlinearities associated with the vessel dynamics. In this case, there exists a dilemma between the accuracy and interpretation of vessel motion models using traditional methods.

In addition, the use of large tankers becomes an important issue since the demand of transportation for crude oil has increased. System identification for large tanker motion dynamics becomes an involved task due to the maneuverability difficulties caused by their bulk. Unfortunately, comparing with the previous investigations of general vessels, promising results of large tanker maneuvering models are short of appearance and mainly focus on controller design rather than motion dynamics identification [18]. Typically, van Berlekom made an excellent seminal research on Esso Osaka tanker model, whereby the hydrodynamic derivatives have been proposed in detail [14].

Recently, in order to overcome the above-mentioned problems, researchers appeal to artificial neural networks (ANNs) in the field of artificial intelligence technology which can be used to establish nonlinear input–output models for ship maneuvering motion effectively. Mahfouz and Haddara [19] applied the ANN and spectral analysis methods to identify the hydrodynamic derivatives in the mathematical model of marine vehicle motions. Moreira and Guedes Soares [20] proposed a dynamic recurrent neural network (RNN) based maneuvering simulation model for surface ships. Rajesh et al. [18] identified an interesting nonlinear maneuvering model of large tankers based on back propagation (BP) neural networks. Certainly, the ANN based system identification method could obtain considerable performance for approximation and generalization. However, the nonlinearities underlying between input and output variables would also be folded into a "black box" which is difficult to be interpreted and understood.

Motivated by the previous reviews, we present a novel constructive multi-output extreme learning machine (CM-ELM) for large tanker motion dynamics identification in this paper. The underlying main idea could be implemented as follows. A group of well established nonlinear differential equations for tanker motion dynamics are used as the reference model for training and testing data generation. In this case, the dynamics identification is equal to a multi-output regression problem that the states, i.e., surge, sway, yaw speed and rudder angle (u, v, r, δ), are input variables, and state derivatives (Δu, Δv, Δr) are taken as multiple outputs. With data samples at hand, it is followed by the promising data-driven learning method term as CM-ELM for multi-output regression. A candidate pool of hidden nodes in the SLFN is randomly generated by the ELM strategy in the initial phase, and then hidden node ranking and model selection from the candidate pool is implemented by a novel improved MRSR (I-MRSR) method and generalization measure. In the last phase, from the elite subset of model selections, the resulting CM-ELM model is randomly selected to update the output weight based on the whole training data. It should be noted that the proposed CM-ELM method ranks and adds candidate hidden nodes chunk-by-chunk, rather than one-by-one, which would reasonably reduce computational burden and accelerate learning speed. Simulation studies on benchmark multi-output regression datasets validate the effectiveness and superiority of the CM-ELM compared with ELM and OP-ELM, *etc*. In order to evaluate the CM-ELM application performance of large tanker motion dynamics identification, comprehensive simulations and comparisons of typical maneuvering scenarios are conducted on sine rudder angle input and zigzag maneuvers. The results demonstrate that compared with the ELM, the CM-ELM based tanker motion model with parsimonious structure achieves much promising identification and generalization performance in terms of both moderate and extreme maneuvering.

The rest of this paper is organized as follows. Section 2 briefly presents preliminary formulations of related works. The main idea and contributions to the CM-ELM including candidate pool generation, I-MRSR based ranking, constructive model selection and generalization measure are unfolded in Section 3. Section 4 implements simulation studies on the CM-ELM for benchmark dataset experiments and applications to tanker motion dynamics identification in detail. In Section 5, conclusions are drawn.

2. Preliminary formulation

In this section, the preliminary formulation of related works, i.e., extreme learning machine (ELM) and multi-response sparse regression (MRSR), will be briefly presented to enhance the foundation knowledge of our proposed learning scheme, which is applied to large tanker motion dynamics identification.

2.1. Extreme learning machine (ELM)

The ELM [1] was originally proposed for the single-hidden layer feedforward neural networks (SLFNs) and was then extended to the generalized SLFNs where the hidden layer need not be neuron alike. In the ELM, the hidden layer need not be tuned. The overall description of ELM for generalized SLFNs is given by

$$f_L(\mathbf{x}) = \sum_{i=1}^{L} \boldsymbol{\beta}_i G(\mathbf{a}_i, b_i, \mathbf{x}), \quad \mathbf{x}, \mathbf{a}_i \in \mathbf{R}^n \tag{1}$$

where $\mathbf{a}_i$ and b_i are the learning parameters of hidden nodes and $\boldsymbol{\beta}_i$ the weight connecting the ith hidden node to the output node. $G(\mathbf{a}_i, b_i, \mathbf{x})$ is the output of the ith hidden node with respect to the input.