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Dual Reduced Kernel Extreme Learning Machine for Aero-engine Fault Diagnosis

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Abstract

In order to improve the sparsity of kernel-based extreme learning machine (KELM), this paper proposed a novel method named dual reduced kernel extreme learning machine (DR-KELM). The proposed algorithm incorporates traditional greedy forward learning algorithm into backward learning algorithm to gain more sparsity and enhance testing time further. Compared to original KELM, the proposed method produces satisfactory performance of pattern recognition with fewer nodes, and reduces diagnostic consuming time from the tests on benchmark dataset. The DR-KELM application to aero-engine fault diagnosis also demonstrate its superior performance with more sparse structure.

Keywords: kernel extreme learning machine, sparsity, forward learning, backward learning, aero-engine, fault diagnosis

1. Introduction

In recent decades, extreme learning machine (ELM), as a popular machine learning algorithm, has attracted much attention from researchers due to its good generalization performance and extremely fast learning speed [1]. ELM was firstly proposed by Huang in 2005, which is aimed for training single-hidden layer feedforward neural networks (SLFNs). Different from traditional artificial neural networks (ANN), the input weights and biases of hidden nodes of ELM are generated randomly instead of exhaustive tuned by gradient descent way, and then computational effort is decreased. ELM has become one of the pop topics in machine learning area due to its simplified topologic structure [2-4]. It is noteworthy that the differences of hidden nodes input parameters initialization will fluctuate the ELM performance [5]. To this end, ensemble and complicated optimization approaches are used to stabilize the initialized network parameters [6-8]. However, these methods lead to the dramatic increase in network structure complexity.

Generally speaking, ELM requires more hidden nodes than neural networks to achieve the same performance since the hidden nodes input weights are randomly assigned [9]. More hidden nodes means larger networks size, which is negative to its effective application in some scenarios of sensitive testing time. Two strategies are pursued to tackle this issue [10-11]. One way is to use constructive algorithms. The incremental ELM is the typical example of this kind, which begins with a small initial network and then gradually adds new hidden nodes until a satisfactory framework is obtained [12]. On the contrary, another approach is to use pruning algorithms, which first train a larger than necessary network and then remove the redundant or less effective hidden nodes one by one [13]. Spares Bayesian extreme learning machine is a typical pruning algorithm, which gains satisfactory sparsity [14].

Kernel method provides a unified and powerful framework for regression and classification in machine learning field, including support vector machines [15], principal component analysis [16], Gaussian process