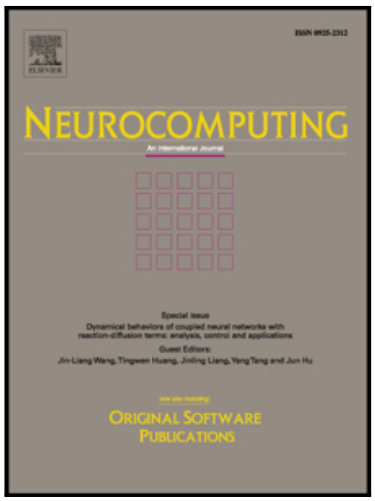


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# An Incremental Neuronal-Activity-based RBF Neural Network for Nonlinear System Modeling

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**Abstract**

In this paper, a novel incremental radial basis function (RBF) neural network is proposed for nonlinear systems modeling. The hidden layer is constructed dynamically on the basis of the neuronal activity (NA), which is measured by the local field potential (LFP) and the average firing rate (AFR), with the goal of enhancing the structural compactness. Simultaneously, a modified second-order algorithm is utilized to train the neuronal activity-based RBF (NARBF) neural network, which can decrease the convergence time and improve the generalization performance. Then, three benchmark nonlinear system modeling simulations are employed to evaluate the proposed NARBF neural network, indicating that the proposed neural network can obtain good generalization performance with a compact structure after fast training. Finally, the NARBF neural network is applied to wastewater treatment process modeling, which demonstrates that the proposed algorithm can predict the key water quality variable precisely.

*Keywords*: RBF neural networks; incremental; neuronal activity; second-order training; nonlinear system modeling

## 1. Introduction

Radial basis function (RBF) neural networks, being inherited from the perceptual model on visual hyperacuity [1], are well-known for the simple topological structure and universal approximation ability. Since the approximation ability has been proved [2], they have drawn much attention to various areas, such as classification, nonlinear system modeling, adaptive control, and so on [3-8]. Nevertheless, RBF neural networks still face challenges and open problems on how to model nonlinear systems accurately and fast [9]. The primary questions for designing RBF neural networks involve two aspects [10]:

1) The construction of a network structure (the hidden layer size and initial parameters)
2) The optimization of all the parameters (centers, radii, and weights).

Structures decide the approximation potentials of RBF neural networks [11]. If the structure size is too large, the network may lose its generalization ability due to over-fitting. Conversely, small number of RBF neurons may cause under-fitting [12]. It is very crucial to construct an RBF network with an appropriate structure size. One conventional approach is to determine the number of RBF neurons by experience or by performing trials. However, such an approach cannot obtain a parsimonious neural network with desirable generalization performance. Clustering methods have been used to handle this issue [13-18]; still, there are two disadvantages when applying them to construct RBF neural networks. First, most of the clustering algorithms must set the class number at the beginning, which means that the structure cannot be determined automatically. Second, the output information is not accounted for during the construction. For the purpose of building a dynamic and compact structure into RBF neural networks, numerous of