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A hybrid evaluation model for flight performance based on bacterial foraging and Elman network

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A B S T R A C T

The evaluation of the flight performance via multiple physiological signals is an important problem in the field of flight safety. A hybrid prediction model is proposed to dispose multiple physiological signals with high dimension in this paper. Main contribution of our model is that of a novel bacterial foraging algorithm (BF) to optimize Elman neural network, which can perform parallel search and escape local minimum easily, and provide better prediction accuracy of the flight performance. Other bio-inspired algorithms such as genetic algorithm (GA), particle swarm optimization (PSO) and chaotic GA are also used to optimize the unknown parameters of the Elman network. Experimental results indicate that the proposed hybrid model based on BF algorithm and Elman network is well suited for the evaluation and prediction of the flight performance. Compared with the other public algorithms, the BF can easily identify the unknown parameters of the established models and has better optimization capability.

1. Introduction

Flight performance, as Y.-H. Lee and B.S. Liu manifested in the paper [1], can be defined by the deviation of flight path. When the flight path deviates from the safe values seriously, accidents may happen. Thus supervising as well as evaluating the flight performance during plane piloting is an important aspect to enhance the safety of civil aviation.

In terms of the flight performance evaluation, traditional approaches are mainly based on the manual assessment [2], such as giving a mark by instructors, which is difficult for the instructors to evaluate objectively. Many scholars have obtained some achievements in the field of flight performance evaluation. B. Johannes et al. [3] established an automated algorithm to assess the flight performance and compared with the expert rated performance and showed the high significant correlation. Zhang Jianye et al. [4] established an auto-assessment system to assess the flight performance using flight data. L. Zhongqi et al. [5] established BP neural networks based on eye movement data to evaluate pilot performance. Based on the reference [5], more physiological features could be considered. Up to now, many researchers have assessed pilot's workload though multiple physiological parameters [6–9]. Studies indicated that some physiological features like heart rate, respiration rate and some eye movement features will change with the variation of workload. Furthermore, Y.-H. Lee and B.S. Liu [1] showed that the pilot's workload could be assessed by the flight performance. It is obvious that when the flight performance becomes poor, the pilot's workload will increase and physiological parameters will change. Thus it can be seen that there exist some relationships between the flight performance and the pilot's physiological features and we can evaluate and forecast the flight performance through multiple physiological parameters.

Multiple physiological signals are characterized by non-linear, high-dimensional, complex structure and are information-related. Artificial neural network (ANN) shows its unique advantages when dealing with large complex non-linear system, especially Elman neural network. Elman neural network is one kind of globally feed-forward network with a context layer in the hidden layer as a delay operator to store internal states, which make the system a dynamic time-varying capacity and strong global stability. But because it inherits some defects of BP neural network, it will fall into local minimum easily. Thus finding an optimization algorithm to train the network is necessary to enhance the performance of the network. In the past years, bio-inspired optimization algorithms have been developed gradually. Genetic algorithm (GA) is an evolutionary algorithm which was put forward in 1975 by J. Holland.

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Through decades of development, it has been widely used in the field of combinatorial optimization, machine learning, signal processing and self-adaptive control [10–12]. Genetic algorithm seeks for the optimal solution by imitating the natural selection and genetic mechanism. It has three basic operators: selection, crossover and mutation. However, the disadvantages of genetic algorithm are the complex programming and long training time. Additionally, it may get stuck at a local optimum and tends to converge prematurely. Particle swarm optimization (PSO) is also an evolutionary algorithm which was proposed in 1995 by Eberhart and Kennedy. It came of the research on bird flock preying behavior. Compared with GA, PSO is easy to implement. But it is not suitable to solve some discrete problem and also easy to fall into the local optimum [20]. Bacterial foraging algorithm (BFA) is a rising evolution algorithm, which was put forward in 2002 by K.M. Passino [13]. It is a global random search algorithm combined with bacterial chemotaxis, swarm interaction and the characteristics of reproduction and dispersedness of bacteria, which can avoid the local minimum and increase the predication accuracy. In the past years, studies on this algorithm have been developed gradually [13–17]. BFA as a rising optimization algorithm has been widely used to deal with complex problems. Reviewing the published literatures about integration of BF and neural network (NN), there are little reports on the integration of bacterial foraging algorithm and Elman neural network [21–23]. Then, this paper will focus on the establishment of hybrid model on the basis of BF and Elman.

By combining the bacterial foraging algorithm with Elman neural network, we put forward a new prediction model for the evaluation of flight performance, called BF-Elman. Section 2 introduces the fundamental theory of Elman and bacterial foraging algorithm, and then proposes a new hybrid model based on BF and Elman for the typical problem of flight safety. Section 3 presents the experimental results and discussion. The final conclusion is drawn in Section 4.

2. Hybrid model of BF-based Elman

2.1. Elman neural network

The Elman neural network is one kind of globally feed-forward network proposed by Elman [18,21–23]. The structure of an Elman neural network is illustrated in Fig. 1. z^{-1} is a step delay operator. It is obvious that the Elman network consists of four layers: input layer, hidden layer, context layer, and output layer. There are adjustable weights connecting every two adjacent layers. Context layers are used to store the internal states, which makes it to have dynamic mapping functions and make the system to have the ability to adapt the time-varying characteristics.

The training algorithm for the Elman neural network is based on the gradient descent principle, similar to the BP learning algorithm. However, the role that the context weights play in the error back-propagation procedure must be taken into consideration in the derivation of this learning algorithm. From Fig. 1, at iteration k we have the following relationship:

$$o\_c_i^{(k)} = net\_c_i^{(k)} \tag{1}$$

where o_c_i and net_c_i are the output and input of context node i, respectively. Note that the node activation function of the context nodes is linear. It can be seen that $w1_{i,j}$ as the weight that connects node i in the input layer to node j in the hidden layer, $w2_{i,j}$ as the weight that connects node i in the hidden layer to node j in the output layer, and $w3_{i,j}$ as the weight that connects context node i to node j in the hidden layer. m, n, l are the numbers of nodes in the input, output and hidden layers, respectively. To calculate the input as well as output of hidden node j, we have

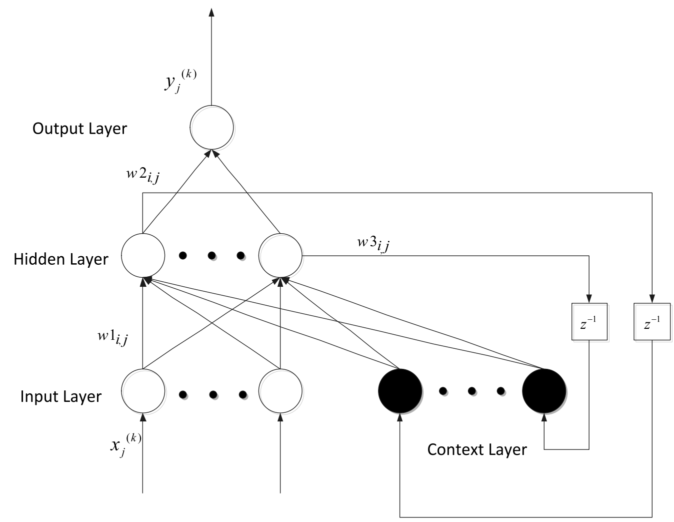

Fig. 1. Structure of Elman neural network model.

$$net\_h_j^{(k)} = \sum_{i=1}^{m} w1_{i,j} x_i^{(k)} + \sum_{i=1}^{l} w3_{i,j} o\_c_i^{(k)} \tag{2}$$

and

$$o\_h_j^{(k)} = a\left(net\_h_j^{(k)}\right) \tag{3}$$

$x_i^{(k)}$ is the input of Elman neural network, where $i = 1, 2, \ldots, m$. net_h_i is the input of node i in the hidden layer, and o_h_i is the output of node i in the hidden layer, where $i = 1, 2, \ldots, l$. The output of node j in the output layer, $y_j^{(k)}$, is given by

$$y_j^{(k)} = \sum_{i=1}^{l} w2_{i,j} o\_h_i^k \tag{4}$$

where $j = 1, 2, \ldots, n$. The output of context node i at the kth training iteration is one-step-delayed output of the corresponding hidden node i:

$$net\_c_i^{(k)} = o\_c_i^{(k-1)} \tag{5}$$

Due to its dynamical properties, the Elman neural network has found numerous applications in such areas as time series prediction, system identification and adaptive control. However, local minimal caused by the regular BP learning algorithm often result in an unavoidably large approximation error that may reduce its prediction accuracy. Integration the bacterial foraging algorithm with the Elman network is a solution to this problem, which is to be introduced in the following sections.

2.2. Bacterial Foraging algorithm

Bacterial Foraging algorithm is a new division of bio-inspired algorithm [13]. This technique is developed by inspiring the foraging behavior of Escherichia coli bacteria, which consists of three principal mechanisms, namely Chemotaxis, Reproduction, and Elimination-dispersal. Each of the process is briefly described as follows:

2.2.1. Chemotaxis

Moving toward to eutrophic areas is called chemotaxis. Chemotaxis process is achieved by through swimming and tumbling via Flagella. Depending upon the rotation of flagella in each bacterium, there are two modes of movement, namely tumble and run. A unit walk with random direction represents a “tumble” and a unit walk