A hybrid CNN-LSTM model based actuator fault diagnosis for six-rotor UAVs

Jiangmeng Fu[1], Cheng Sun[1], Zhen Yu[1] , Lijun Liu[1],

1. Department of Automation, School of Aerospace Engineering, Xiamen University, Xiamen 361005
E-mail: liulijun@xmu.edu.cn

Abstract: With the development and popularity of multi-rotor UAVs, actuator fault diagnosis in multi-rotor UAVs has become more and more important. This paper proposes a deep-learning-based method to accurately locate actuator faults by using flight data of a real UAV. The proposed method splits the UAV's data into smaller pieces and then extracts features by one-dimensional convolutional neural network (1D-CNN), and explores internal connections of the UAV's time series data by adding the long short-term memory (LSTM). So, a hybrid CNN-LSTM model is developed for the fault diagnosis of actuator faults. Experiments show that the average accuracy of fault diagnosis of the hybrid CNN-LSTM model is 92.74%, which is better than that of other models, such as the CNN model, the LSTM model, and the deep neural network (DNN) model.

Key Words: Six-rotor UAV, Convolutional neural network, Long short-term memory, Fault diagnosis, Deep learning

1 INTRODUCTION

With the advancement of technology, UAVs are becoming more and more popular. According to statistics, in 2017, about 3 million drones were sold worldwide, and more than 1.1 million UAVs were registered in the US Federal Aviation Administration. About 220,000 UAVs, excluding many private flights, are registered with the real name in the Civil Aviation Administration of China. Among them, the six-rotor UAVs have advantages in fault tolerance and load capacity [1]. However, minor faults should be diagnosed at early stage even if the six-rotor UAVs have high fault tolerance, because the accumulation of minor faults will lead to serious problems, such as the crash of UAVs.

An actuator block consists of three main parts: electronic speed controller, motor and blade. Minor faults in any part of these three parts will result in insufficient power output. In such case, the six-rotor UAVs can still fly, but the stability and attitude adjustment will be slightly different from the normal UAV. The actuator fault diagnosis for multi-rotor UAVs has always been studied. R. Vepa et al. proposed expert systems to diagnose fault of flight control systems [2]. This method is not very versatile and lacks self-learning and adaptation. It cannot deal with minor actuator faults in six-rotor UAVs. Then the model-based methods such as the combination method based on parity space and wavelet transform and the method based on two-stage Kalman filter [3] have been proposed, but these methods need to establish an accurate six-rotor UAV model. Adam et al. proposed fault diagnosis based on signal processing in case of blade damage, and finally located the shaft by an SVM classifier [4]. That is like the case studied in this paper. However, Adam considered the vibration signal under the unilateral damage of the blade, which could not include the minor faults of the whole actuator block. What is more, such unilateral damage fault was relatively special, which could easily cause the disintegration of the rotor. Previous studies on actuator fault diagnosis for UAVs are roughly divided into three types: model-based methods [5], signal-based methods [6], and knowledge-based methods [7]. The knowledge-based approach is widely accepted as an effective solution. When it comes to the extraction of required features from data, there is a very popular method called neural networks in recent years. Neural networks are good at simulating complex systems and then launch a series of operations on inputting signals and data. Some people have used neural networks to diagnose mechanical faults and achieved very good results. In neural networks, convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have been widely applied in recent years. CNN has good performance in time-series prediction [8] and image recognition [9]. A variant of RNN called long short-term memory (LSTM) networks has made breakthrough in time series problem such as speech recognition [10] and traffic forecast [11] in recent years.

In the previous research, minor faults of actuators cannot be diagnosed with high diagnostic accuracy in a six-rotor UAV's real flight. The main contribution of this paper is to propose a fault diagnosis method based on a hybrid neural network model of one-dimensional convolutional neural network and long short-term memory neural network. This method can accurately locate the actuator faults. This paper analyzes the way to construct a data set and then uses the proposed hybrid CNN-LSTM model [12] to complete the actuator fault diagnosis according to the data characteristics. Through the comparison of a series of experiments, it is proved that the proposed hybrid CNN-LSTM model is superior to the CNN model, the LSTM model, and the DNN model for actuator fault diagnosis in six-rotor UAVs.

The remainder of this paper is organized as follows: Section 2 introduces CNN and LSTM. Section 3 presents the method with the hybrid CNN-LSTM model for fault diagnosis of actuator fault in six-rotor UAVs. Section 4 details the experimental process and discusses the

This work is supported by the National Natural Science Foundation of China under Grant 61304110, the Fundamental Research Funds for the Central Universities under Grant 20720160081, the Guangdong Natural Science Foundation under Grant 2018A030313124, and the Natural Science Foundation of Shanghai under Grant 18ZR1443200.

978-1-7281-0106-4/19/$31.00 ©2019 IEEE

experimental results, and the final section presents a prospect for future research.

2 CONVOLUTIONAL NEURAL NETWORK AND LONG SHORT-TERM NETWORK

2.1 One-dimensional convolutional neural networks

Convolutional neural networks [13] is a kind of neural network.A convolutional neural network generally includes input layer, convolution layer, pooling layer, full connection layer and output layer. The most important building block is the convolution layer. Moreover, the feature map in convolution layer can be expressed as follows.

$$m_{ij}^{k} = f((W * x)_{ij} + b^{k}) \tag{1}$$

Where m^k denotes the k^{th} feature map in layer m. Moreover, W denotes the values of the corresponding filter's weight. In addition, b^k is the bias of the neurons in a feature map. The pooling layer is usually added after a convolution layer in order to reduce the number of parameters and limit the risk of overfitting. Generally, the pooling layer includes two types, average pooling and maximum pooling, which respectively represent the extraction of local mean value and the extraction of local maximum value.

2.2 Long short-term memory

Long short-term memory [14] is a special kind of recurrent neural network (RNN), which is proposed to solve the vanishing gradient problem in recurrent neural networks. We can represent this tiny network against the time axis, as shown in Fig. 1.

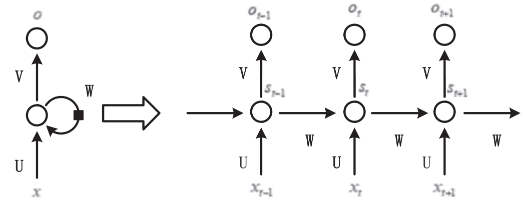

Fig 1.A recurrent (left), unrolled through time (right).

In Fig. 1, t indexes the time-stamp, x_t is the input vector at time step t, s_t is the vector in the hidden layer at time step t, o_t is the output vector at time step t. Each recurrent neuron has two sets of weights: one for the input vector and the other for the outputs of the previous time step. We can call these W_{xs} and W_{ss} . The output of a single recurrent neuron can be computed as Eq. (2) and Eq. (3) (b is the bias term and $H(\cdot)$ is the activation function, e.g., tanh).

$$s_t = H(W_{xh}x_t + W_{hh}s_{t-1} + b_h) \tag{2}$$

$$o_t = W_{ho}s_t + b_o \tag{3}$$

The internal details of long short-term memory networks are shown in Fig. 2.

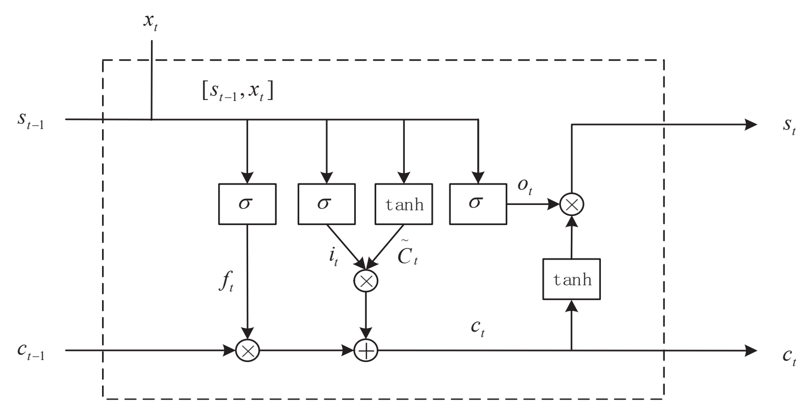

Fig 2. Computation Flow Diagram of Long Short-Term Memory Model.

The structure of LSTM cell can be described by the following equations:

$$f_t = \sigma(W_{xf}x_t + W_{sf}s_{t-1} + b_f) \tag{4}$$

$$i_t = \sigma(W_{xi}x_t + W_{si}s_{t-1} + b_i) \tag{5}$$

$$c_t^* = \tanh(W_{xC}x_t + W_{sC}s_{t-1} + b_C) \tag{6}$$

$$o_t = \sigma(W_{xo}x_t + W_{so}s_{t-1} + b_o) \tag{7}$$

$$c_t = f_t \odot c_{t-1} + i_t \odot c_t^* \tag{8}$$

$$s_t = o_t \odot \tanh(c_t) \tag{9}$$

Where the subscript t indexes the timestamp, i_t f_t and o_t are input gate, forget gate and output gate. The σ generally represents a sigmoid function, and $\odot$ denotes the convolution operator.

3 DESIGN OF THE HYBRID CNN-LSTM MODEL

The six-rotor UAVs have six power shafts, each of which consists of three main parts: electronic speed controller, motor and blade. Minor faults in any part of these three parts will result in insufficient power output. This paper mainly focuses on the study of minor faults in the actuators under normal running. However, minor faults should be diagnosed at early stage, because the accumulation of minor faults will lead to serious problems. Therefore, we need to find a universal way to locate the actuator faults accurately.

Based on knowledge and experience, we selected eleven possible related characteristic quantities as the input of model. Moreover, they are shown in table 1. The data at a certain moment can only represent the instantaneous state of a UAV, while the instantaneous state cannot represent the overall health status of a UAV. We split all of the data into small pieces. In this method, the time step is 200ms. First, a convolution layer is added after the input layer. Then the data is scaled by the down-sampling layer and be inputted into the LSTM layer [14]. There are 32 convolution kernels in the convolution layer, 256 cells in the LSTM layer, and the pooling kernel is two in the pooling layer. After passing through the LSTM network, it accesses the full connection layer, which has 128 cells. The last layer is the output layer, which is a softmax layer. In addition, the output layer contains 7 cells, the NO.0 represents the normal case of the UAV, and NO.1 to NO.6 respectively represents the minor faults of a certain actuator. The hybrid CNN-LSTM model proposed in this paper is shown in Fig. 3.

Table 1. Input data

DATA TYPE	NAMES
Attitude Angle	roll, pitch
Attitude Angle Rate	rollrate, pitchrate, yawrate
Motor Input	out0, out1, out2, out3, out4, out5

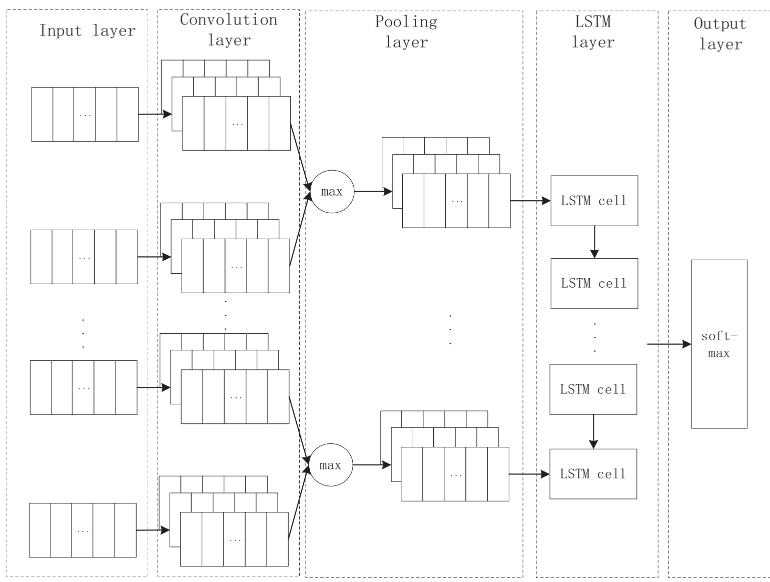

Fig 3. The structure of the hybrid CNN-LSTM model in this paper

4 EXPERIMENT AND RESULT ANALYSIS

4.1 Construction of experimental data sets

To verify the validity of the method, the data set is constructed first. The specific steps to build the flight data set are as follows:

(a) Set up the experiment platform (as shown in fig. 4) and design a simulation of the minor fault in actuators. In the simulation process, we replaced the normal blade with the damaged blade (as shown in fig. 5) to reduce the output power of a certain shaft, cutting both end of blade by 3cm when the entire blade length was 30cm. The designed simulation of the fault has little influence on the UAV's stability.

(b) Split the data set. In order to ensure the comprehensive diversity of our training and test samples, we constructed four data sets during the experiment. Each data set contains 13, 300 training examples and 2, 100 test examples. The training set contained 1900 examples under normal condition and 1900 examples from each actuator with minor faults, which ensures equal participation from all of the classes. 20% was separated from the training set for the purposes of validation. And the test set contained 300 examples under normal condition and 300 examples from each actuator with the minor faults.

(c) Data preprocessing. Since there are different dimensions between the input data, we need to unify dimension. In general, the most common method to unify dimension is Min-Max normalization, which unifies the data to the range [0, 1]. There will be many negative numbers in a six-rotor UAV's data. These negative numbers generally represent different directions, which is of great help to the actuator fault diagnosis in UAVs. Therefore, we adopt different methods to unify dimension according to the data characteristics. Firstly, the Min-Max normalization method is adopted for the data related to motors. This method is achieved by finding the maximum and minimum value in the batch, and then normalization is performed with Eq. (10). For the data related to attitude, we find the maximum absolute value in the batch, and then normalize the data to [-1, 1] through Eq. (11).

$$x^* = \frac{x - \min}{x - \max} \tag{10}$$

$$x^* = \frac{x}{\max} \tag{11}$$

Fig 4. The UAV based on pixhawk used in experiments.

(a)

(b)

Fig 5. Figure (a) is the normal blade, and figure (b) is the blade that simulates the minor actuator fault in experiments.

4.2 Results and analysis of experiments

In this paper, a hybrid CNN-LSTM model is proposed for the actuator fault diagnosis in six-rotor UAVs. To begin with, we design a neural network consists of an input layer, a convolution layer, a pooling layer, a LSTM layer, a full connection layer and an output layer in the experiment. In addition, basic parameters of the proposed neural network are selected from the best result based on relevant experiments and experience. Among them, the loss function adopts the cross-entropy function, which is defined as follows.

$$loss = \sum_i (y_i \cdot \log(y_i^*) + (1 - y_i) \cdot \log(1 - y_i^*)) \tag{12}$$

Where y_i are the label, y_i^* are the predicted value. The neural network adopts the mini-batch training. Other parameters of the model are shown in Table 2.

Table2. Basic parameters in the model

PAREMETER	VALUE
batch-size	128
epoch	100
optimizer	Adam
activation	tanh

In the experiment, dropout is added to each layer of proposed models to increase the diagnosis accuracy rate on test data. As a result, the neural network cell will be discarded with a certain probability (the value of dropout is 0.3 in this paper) during connection, so different neural networks are trained indirectly. Therefore, the overfitting problem of large-scale neural networks is improved in many cases.

Experiments were carried out by using the hybrid CNN-LSTM model, the CNN model, the LSTM model and the DNN model respectively, and each of their loss function uses the cross-entropy function. The relationship between the loss value and the epoch of different model on training data is shown in Fig. 6. According to the information shown in figure, the hybrid CNN-LSTM has the better performance. The next is the LSTM model. The loss value of LSTM model was slightly higher than the hybrid CNN-LSTM model, followed by the CNN model and the DNN model.

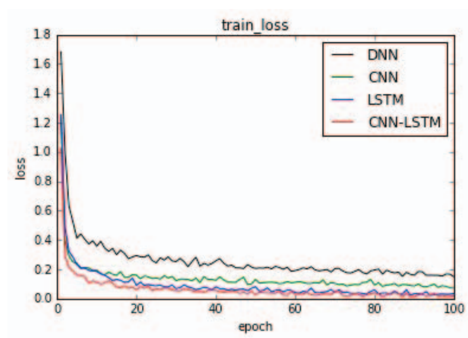

Fig 6. The loss value of different model on training data.

Further experiments were carried out to train each model on four constructed data sets, and the accuracy of each network on test sets was compared. The results are shown in Table 3. We can know that the hybrid CNN-LSTM model is superior to the other three models on each data set. The table shows that the average accuracy of the hybrid

CNN-LSTM model is 92.74%, the average accuracy of the LSTM model is 91.22%, the average accuracy of the CNN model is 89.08 %, and the average accuracy of the DNN model is 85.20%.

The experimental results show that the hybrid CNN-LSTM model has higher diagnosis accuracy than the other three models. CNNs can automatically extract effective features from UAV data, which is very effective for the actuator fault diagnosis for UAVs. The six-rotor UAV is subject to a lot of interference during flight, and CNNs have the function of removing noise. Therefore, the CNN layer is put after the input layer makes a better performance. In addition, the data was split into smaller pieces to acquire a higher diagnostic accuracy based on the UAV's long-term comprehensive state. And the LSTM can deeply explore the internal connection of the UAV's long-term data. In this paper, the two models are combined and successfully be applied to the actuator fault diagnosis for a six-rotor UAV.

Table 3. Diagnostic accuracy of each model on different data sets

dataset	diagnostic accuracy			
	DNN	CNN	LSTM	CNN-LSTM
dataset 1	87.12%	90.89%	92.36%	94.12%
dataset 2	85.20%	88.23%	91.76%	92.95%
dataset 3	83.15%	87.38%	89.25%	90.83%
dataset 4	85.32%	89.81%	91.52%	93.04%
average	85.20%	89.08%	91.22%	92.74%

5 CONCLUSION

There are still many problems in actuator fault diagnosis for multi-rotor UAVs. This paper proposes a deep learning method based on the hybrid CNN-LSTM model for the actuator fault diagnosis in six-rotor UAVs. The proposed method can automatically extract features and find the internal connection of the UAV's data, and thus establishes an effective model to diagnose fault. Experiment results show that the hybrid CNN-LSTM model has better performance on the actuator fault diagnosis than other models, such as the CNN model, the LSTM model, and the DNN model.

In the future research, more sample data sets will be collected and analyzed. Moreover, a better model will be designed for fault diagnosis based on the characteristics of a UAV's data. But there is a problem to be solved in the future regarding noise elimination of drone data, because noise may reduce the fault diagnosis accuracy of a neural network.

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