A Deep Learning Method for Multiple Faults Detection and Classification of Unmanned Ground Vehicles

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ABSTRACT
Due to the increased complexity in actuators and sensors, unmanned ground vehicles have a better chance to generate faults in the course of operation. An untreated fault can result in a failure, which may lead to catastrophic consequences. In this paper, we propose a deep learning method using both input and output signals of the vehicles to learn the features of different faults reflected in the dynamic models of unmanned vehicles. We have applied the proposed method to detect and classify multiplicative and additive faults, as well as the faults that result in malfunction of the actuators. The results show that the proposed deep learning method can accurately detect and classify multiple types of faults, which are caused by different sources.

Keywords
Deep learning, convolutional neural network, fault detection and classification, dynamic system, unmanned ground vehicle

1. INTRODUCTION
Unmanned ground vehicles (UGVs) can be used for many applications where it may be inconvenient, dangerous or impossible to have a human driver present. Normally UGVs are equipped with multiple sensors and actuators. In recent years, the number of sensors and actuators on UGVs has been increasing. As a result, the chance of faults occurring increases. Many fault diagnosis algorithms have been proposed to ensure the safe operation of the vehicle. In the literature, the research on fault detection and classification has been active over the past thirty years. With more and more advanced control algorithms, there is a growing demand for fault tolerance, which can be achieved not only by improving the individual reliabilities of the functional units but also by efficient fault detection, isolation and accommodation [1, 2].

Deep learning, which refers to representation learning with multiple layers of nonlinear transformation [3], has been developed to tackle problems in fault detection and fault tolerance for different applications. Compared with traditional fault detection methods such as system identification method, Deep Neural Network (DNN) based fault detection can achieve faster and more accurate results [4]. Unlike traditional machine learning methods, DNN consists of many deep layers to extract high-level representations from the original inputs. The output of hidden layers contains the features of different levels. Compared with traditional shallow models, which have the problems of lacking expression capacity, using deep learning theory can effectively extract characteristics and accurately recognize the health condition of the components. As a result, fault diagnosis and prognosis based on deep learning have been an active, productive and promising research field.

Since the deep belief network (DBN) was applied to aircraft engine fault diagnosis by Tamilselvan in 2013 [5], more and more scholars have applied deep learning to the field of fault diagnosis and prognosis, and obtained many research results. In [6], the authors proposed a new algorithm for detecting and identifying faults. The most important innovations are image-based processing and classification using deep neural networks. They also used time-frequency graphs to represent the one-dimensional signal. In [7], a fault-tolerant control method based on deep learning is proposed for the multi-displacement sensor fault of a wheel-legged robot with a new structure. Unlike most methods that only detect a single sensor, the proposed method can detect a large number of sensors simultaneously and rapidly. In [8], Deep Auto Encoders (DAEs) are developed to automatically and accurately identify bearings faults. The experimental results show that the proposed method can remove the dependence on artificial feature extraction and overcome the limitations of individual deep learning model, which is more effective than other intelligent diagnosis methods. With the development of wind power, the faults in wind turbines are increasing year by year. In [9], based on the strong perception and self-learning ability of deep learning theory, a fault diagnosis method of wind turbine gearbox based on deep belief network and vibration signal is proposed and tested.

The development of deep learning models for fault diagnosis of unmanned ground vehicles has been initiated, with more work anticipated in the near future. There are three main DNN types (i.e., CNN, DBN, and DAE) that can be used for deep learning and feature extraction. DBNs and DAEs can conduct unsupervised pre-training on the weights, which can ease the difficulty of the subsequent supervised training of the deep networks. However, a key problem in DBNs and DAEs is that there are too many weights to train when the inputs are raw signals or their time-frequency representations. In contrast, convolutional neural networks (CNNs) can reduce the number of weights to be optimized using the strategies of local receptive field and weight sharing, which can be effective for reducing computational burden during the training process. In this paper, we will use CNN for the learning and testing.

Vehicle faults can occur in actuators, plant dynamics or sensors. Model-based fault detection diagnosis is one major branch of the fault detection and diagnosis for unmanned ground vehicles. In [10], we proposed a deep learning method for fault detection for autonomous vehicles. The results show that the algorithm can efficiently detect model faults in the system. The new contributions of this paper include: 1) applying the deep learning based algorithm to the general multiplicative and additive faults in the vehicle system dynamic model, and 2) using both system input signals and output signals as the inputs to the DNN to improve the performance of fault detection. To the best of our knowledge, it is the first time in the literature to incorporate the input signals into the inputs of DNN for fault classification for autonomous ground vehicles.

The rest of paper is organized as follows: Section II will describe the system dynamics and fault models of an over-actuated electrical vehicle. Section III will propose a deep learning based fault detection and classification method. Section IV shows the experimental results. Finally in Section V, we conclude the paper and give a few future research directions.

2. SYSTEM DYNAMICS AND FAULT MODELS

The target vehicle is a four-wheel independently driven and steered system [15]. The equations of motion for lateral and yaw motion are obtained as follows:

$$M(\dot{V}_y + \gamma V_x) = 2C_x\left(\delta_f - \frac{V_y + l_f r}{V_x}\right) - 2C_r\left(\frac{V_y - l_r r}{V_x}\right) + \delta F_y (1)$$

$$I\dot{\gamma} = 2l_f C_f\left(\delta_f - \frac{V_y + l_f r}{V_x}\right) + 2l_r C_r\left(\frac{V_y - l_r r}{V_x}\right) + \delta M_z$$
(2)

where $\delta_f \in R^{1x1}$ is the front steering angle input from the driver, δF_y and δM_z are control lateral force and control yaw moment, respectively.

From equations (1) and (2), the state-space equation can be obtained as follows:

$$\dot{x}(t) = Ax(t) + Bu(t)$$
(3)

$$y(t) = Cx(t) + w(t)$$
(4)

where $x \in R^{nx1}$ is the state variable, $u \in R^{mx1}$ is the control input, $y \in R^{px1}$ is the measurement output, $w \in R^{px1}$ is the measurement noise.

2.1. Fault Models

In this study, we investigate the detection of three different actuator faults in vehicles. Fault 1 is the combination of an additive fault and a multiplicative fault. Fault 2 is a multiplicative fault on the electric motor. Fault 3 is an additive fault on the electric motor. Therefore, there are 4 scenarios: without fault, with multiplicative fault, with additive fault, and with both faults.

Equations for multiplicative and additive faults [11-13] are as follows:

$$\dot{x}(t) = Ax(t) + B[(I + \alpha)u(t) + f_u]$$

where $\alpha \in R^{mxm}$ represents the multiplicative actuator fault and is a diagonal matrix with the diagonal elements $\alpha_{ii}, i = 1, \ldots, m, -1 < \alpha_{ii} < 0, I$ is the identity matrix. The additive actuator fault is represented by $f_u \in R^{mx1}$. It is assumed that faults are time-invariant.

3. DEEP LEARNING METHODOLOGY

3.1. Motivation

Faults can occur in unmanned ground vehicles due to electrical or mechanical failures. Without a driver in the vehicle, who can identify different faults and take appropriate measures, the unmanned ground vehicle needs to incorporate fault detection and classification algorithms in the system design.

In this paper, we employ simulated data to validate our proposed method. We will first use the vehicle system dynamic model and fault models to generate simulated data, i.e., the system input signal and the output signals. Then one input signal and two output signals will be transformed to 2D signals through wavelet transform. These three-channel 2D signals are fed to a deep neural network for fault classification. The output of the network indicates whether the signal has no fault, fault 1, fault 2 or fault 3.

3.2. Data Generation and Preprocessing

We use square wave signals with different noises as the input to the wheel motors. For each sample data, uniform noises with the amplitude of 0.5 are added to input control signal *u(t)*, which is fed into the system dynamic and fault models to generate two outputs $y_1(t)$ and $y_2(t)$ for each scenario. Fault parameters are set to be $\alpha_{ii} = -0.45, f_u = -0.55$. We have generated 4000 sample data for training with 1000 samples for each scenario. Figs.1-3 show a typical example of input control signal and corresponding output signals. Fig. 1 shows the system input signals with faults and without a fault. Fig. 2 shows the system output signal lateral velocity $y_1(t)$ for all four scenarios: without a fault (green), with fault 1 (blue), with fault 2 (yellow), and with fault 3 (pink). Fig. 3 shows the system output signal yaw motion $y_2(t)$ for all four scenarios: without a fault (green), with fault 1 (blue), with fault 2 (yellow), and with fault 3 (pink).

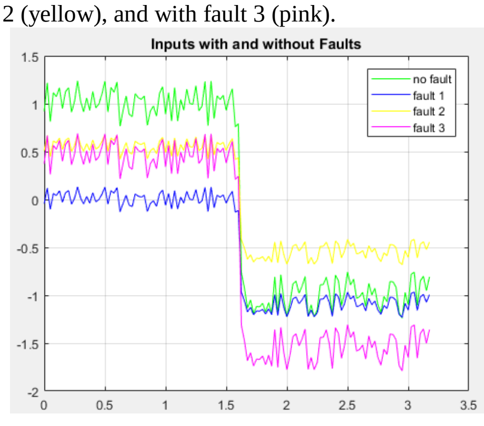

Fig. 1. The system input signals with faults and without a fault

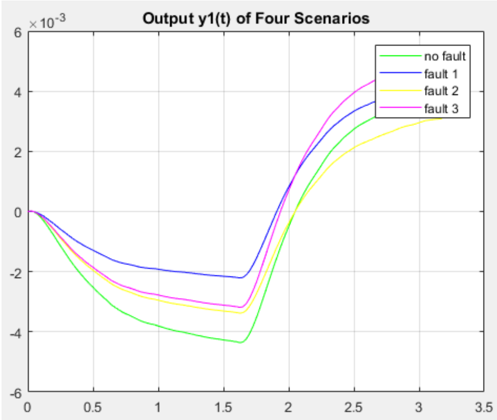

Fig. 2. The system output signal $y_1(t)$ for all four scenarios: without a fault (green), with fault 1 (blue), with fault 2 (yellow), and with fault 3 (pink).

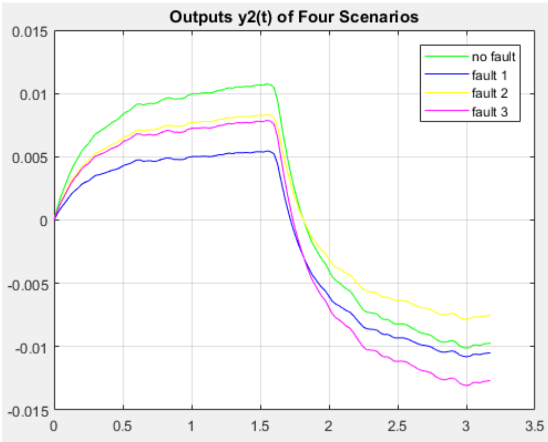

Fig. 3. The system output signal $y_2(t)$ for all four scenarios: without a fault (green), with fault 1 (blue), with fault 2 (yellow), and with fault 3 (pink).

In this paper, we propose to use continuous wavelet transform (CWT) to transform the 1D input/output time-domain signals $u(t)$, $y_1(t)$, $y_2(t)$ into the corresponding 2D time-frequency domain images, respectively, which are then composed to a 3-channel RGB image I to feed to DNN as inputs, as shown in Fig. 4. By adding frequency domain information to the time domain data, the inputs to DNN contain more salient features and as a result, make it easier to identify faults [10].

3.3. Deep Neural Networks

One traditional fault detection technique is to use system identification and robust residual generation [2, 14, 15, 16]. Since system identification-based detection methods require more restrictive input signals to obtain accurate system models, we can use deep learning in the areas, where system identification is not efficient.

Deep neural networks are a machine learning technique, which has the capability to model complex, highly nonlinear relationships between the DNN input and fault classification. Based on prior domain knowledge and a large amount of training data, deep learning can be a powerful and effective tool to detect and classify different complex faults in vehicles, which will significantly improve the quality and the speed of the fault decision process. To be specific, deep learning can enable a hierarchical nonlinear learning of high-level features built on top of low-level features to detect which fault(s) are present. Low-level features are the basic details of faults or feature patterns, whereas high-level features are more abstract, that is, high-level features can be obtained by a series of nonlinear transformations through multiple deep layers.

We train the weights of the deep neural network with 10 layers, as shown in Fig. 4, which minimize the loss function $J(w)$. The size of the normal and fault images is 512 x 512 x 3 as DNN inputs. The ground truth classification labels of the images both normal and faults are fed to the DNN and compared with the classification decision from the trained DNN model.

The loss function $J(w)$ is defined as follows:

$$\min_{w} J(w) = \sum_{n=1}^{N} \left(\left| y_n(I_n, w) - y_{tn} \right| \right)^2$$

where n corresponds to the n-th sample of training data, N is the number of training samples, w is all the parameters of the deep neural network, y_{tn} is the ground truth label 0 for normal class, 1 for fault 1, 2 for fault 2, 3 for fault 3.

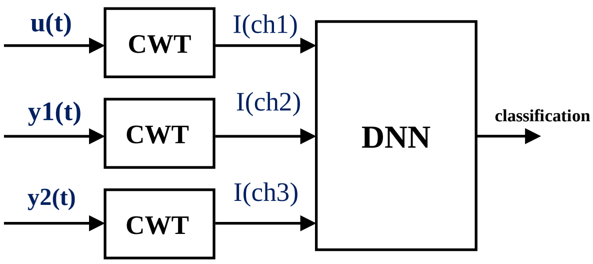

Fig. 4. The schematic of DNN fault detection and classification

4. RESULTS

The models of many sub-systems of the vehicle are known. System identification methods can be used to obtain the dynamic models when the models are unknown. In this paper, we consider the multiplicative and additive faults that may be caused by mechanical or electrical problems. We use the system dynamics and fault models of an unmanned ground vehicle to simulate vehicle faults to generate data for training and testing. In order to detect and classify the faults of the UGVs, we propose to use the DNN model based on only the input and output signals of the vehicles.

In [10], the DNN was fed with only output signals for fault detection. In this paper, we employ both input signals and output signals. This is crucial for the fault classification because the combination of input and output signals may provide more unique features of the system dynamics, with faults and without faults. Moreover, the input distribution may not be unique for achieving the same output. Using the combination of the input and the output signals as DNN inputs will eliminate the ambiguity of the data inputs.

4.1. Fault Classification

In this section, we validate the performance of our proposed DNN fault classification technique. We use a separate test dataset of 2000 images (500 normal images, 500 defect 1 images, 500 defect 2 images and 500 defect 3 images) to test the proposed DNN fault classification. The result is shown in Table 1. In this study, we have demonstrated that the proposed DNN technique can effectively detect the faults caused by a mechanical vehicle wheel control failure.

Table 1: Fault Classification Results

TEST DATASET	DETECTION CORRECT RATE
500 NORMAL SIGNALS	99.00%
500 FAULT 1 SIGNALS	100.00%
500 FAULT 2 SIGNALS	100.00%
500 FAULT 3 SIGNALS	98.40%
AVERAGE	99.35%

5. CONCLUSION AND FUTURE WORK

In this paper, we have demonstrated that the proposed deep learning method has the ability to effectively perform multi-fault detection and classification tasks for unmanned ground vehicles. In the future, we will extend the algorithm for more types of faults and investigate the fault tolerance control algorithms for unmanned ground vehicles as well.

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