Sensor and Actuator Fault Diagnosis

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Contributor: Jinghui Pan

Sensors and actuators are key components in the robot system, but their working environment is very complex, with electromagnetic interference, vibration, etc., which will affect the output of the sensors and then the actuators. Moreover, the variable load on manipulators is also a challenge for system state feedback or estimation. All of the above factors make the faults diagnosis of robot system sensors and actuators an urgent task. The DCNN is used to deal with sensor and actuator faults of robot joints, such as gain error, offset error, and malfunction for both sensors and actuators, and different fault types are diagnosed using the trained neural network.

Keywords: fault diagnosis ; sensor fault ; actuator fault ; deep convolutional neural network ; robot joints

1. Overview

The DCNN is used to deal with sensor and actuator faults of robot joints, such as gain error, offset error, and malfunction for both sensors and actuators, and different fault types are diagnosed using the trained neural network. In order to achieve the above goal, the fused data of sensors and actuators are used, where both types of fault are described in one formulation. Then, the deep convolutional neural network is applied to learn characteristic features from the merged data to try to find discriminative information for each kind of fault. After that, the fully connected layer does prediction work based on learned features. In order to verify the effectiveness of the proposed deep convolutional neural network model, different fault diagnosis methods including support vector machine (SVM), artificial neural network (ANN), conventional neural network (CNN) using the LeNet-5 method, and long-term memory network (LTMN) are investigated and compared with DCNN method. The results show that the DCNN fault diagnosis method can realize high fault recognition accuracy while needing less model training time.

2. Robot Systems

With the development of robot and control technology, various robots are widely used in industry. Different applications present specific requirements for robot systems, such as rapidity, robustness, and safety [1][2][3]. However, among all the indices required by applications, the controllability of the robot in fault state has become the most critical factor. Fault identification is the precondition for realizing this goal, which promotes the investigation of our research [4][5][6].

Robot systems cannot work without the support of different kinds of sensors and actuators. Miniaturization and multi-functionality are required for development. The rapid development of sensors, material science, and micro-electro-mechanical technology allows modern robot joint modules—such as hollow motor, servo driver, harmonic reducer, brake, and encoder—to be integrated within limited space [7]. Sensors and actuators are key components in the robot system, but their working environment is very complex, with electromagnetic interference, vibration, etc., which will affect the output of the sensors and then the actuators. Moreover, the variable load on manipulators is also a challenge for system state feedback or estimation. All of the above factors make the faults diagnosis of robot system sensors and actuators an urgent task [8].

In most robot system faults, sensor and actuator malfunction are the main causes of robot system failure. Therefore, diagnosis for the sensors and actuators is very important. In order to improve the reliability of robot joints and realize fault detection and fault-tolerant control of robot systems, researchers have been focused on fault detection and fault-tolerant control of robot joints for many years, and many practical fault diagnosis methods have been proposed. In [9], redundant sensors are used on the robot joint, and then fuzzy rules are designed to adjust the threshold of the fault signal adaptively to carry out fault diagnosis. In [10], for a six-degree-of-freedom robot joint system, low-cost MEMS magnetic, angular velocity, and gravity sensors are used to estimate the joint angle of a rotating manipulator. In [11], a discrete-time framework for fault diagnosis of robot joint sensors, force or torque sensors, and actuators is proposed. The redundant sensors are used on the robot joint, and the feedback values from redundant sensors and the estimated values calculated by two isolation observers are input into the fault decision system. The data from redundant sensors are used to provide information for a group of diagnostic observers to detect, isolate, and identify faults of joint actuators, force, or torque sensors.

However, there may be another consideration when using redundant sensors for fault diagnosis. A robot fault diagnosis system based on redundant sensors not only increases structural complexity, but also increases the hardware cost of the system. In addition, redundant sensors also increase the probability of a sensor fault when the running time of a robot system approaches the sensor's life cycle.

In order to overcome the shortcomings of using redundant sensors for fault diagnosis, observers have been widely used. There are many novel theories that could be used to design state observers for robot fault diagnosis. A robot-fault diagnosis method using fuzzy logic is proposed in [12] to evaluate residuals. Fuzzy logic applied to robot fault diagnosis does not require any redundant sensors, but it relies on the fault model of the robot system. The sliding mode method can be seen everywhere in robot fault diagnosis. Daniele uses a second-order sliding mode observer for fault detection and isolation of the rigid manipulator of the COMAU robot and uses the suboptimal second-order sliding mode algorithm to design the input law of the proposed observer, which can detect a single fault on a specific brake or a specific sensor of the manipulator [13]. Since the high order sliding mode observer can detect possible faults in specific parts of the robot system, the sliding mode method is greatly expanded [14]. The observer design methods mentioned above are just some typical representatives, actually, there are many other methods that could be used for robot fault diagnosis, such as the output feedback method [15], nonlinear disturbance observer [16], and feedback linearization disturbance observer design method [17]. As it is well known, the difficulty of observer-based robot fault diagnosis lies in the gain design process [18].

Machine learning introduces an effective solution to the above problems caused by redundant sensors and observers. Typical application methods include, but are not limited to, genetic algorithm [19], support vector machine [20], cluster analysis [21], and neural network [22]. Among them, the neural network is widely used in the field of fault diagnosis because of its superior nonlinear fitting ability. Traditional methods of fault diagnosis manually realize feature extraction, so prior knowledge about fault information is needed, which increases the difficulty of analyzing the results. Neural networks, especially deep learning methods, can learn representations and patterns hierarchically from the input data, and realize effective feature extraction, so the deep learning method has the ability to model complex working conditions and output accurate predictions. Several typical deep learning methods have been successfully applied to fault diagnosis [23][24][25][26], including autoencoders [27], deep belief networks [28], and CNN [29]. The autoencoders and feature ensemble method is applied in actuator fault diagnosis [30]. Furthermore, the one-layer autoencoder-based neural network is proven to be effective in the task of fault classification [31]. The deep belief nets model is successfully applied for fault diagnosis in actuators using vibration signals [32]. One-dimensional CNN is used to analyze the raw time series data of the actuator and proved to be successful in diagnosing fault states [33], and a new CNN architecture based on LeNet-5 is set to process the bearing data set [34].

Considering that the output of sensor and actuator are similar when faults occur, the normal neural network fault diagnosis methods cannot exactly tell the difference between them. In this paper, the DCNN is used to diagnose sensor and actuator faults of robot joints. DCNN can extract the features from the input data and realize fault classification by increasing the depth of the network. In addition, flexible selection of convolution kernel width makes it an efficient way to deal with classification problems with weak characteristics. Actually, there may be many types of sensors and actuators; our research mainly focuses on the problems of fault diagnosis in position sensors for the robot joint and torque sensors for the actuator. The robot joint is forced to move in a sinusoidal trajectory with the control of actuator, and the position sensor feeds back corresponding signals under different sensor states. Position sensor and torque sensor are separately denoted by sensors and actuators in the following main text.

3. Conclusions

The DCNN fault diagnosis method is used to recognize the sensor and actuator faults of the robot system. The robot sensor and actuator output data are fused. In order to increase the number of training samples, the fault data set is expanded way of the data set enhancement method, and then the fault diagnosis is carried out using a deep convolution neural network. SVM, ANN, CNN, and LTMN-based neural network fault diagnosis methods are compared with the proposed DCNN and conclusions can be drawn that DCNN can better extract the fault information from the original input data and makes a more accurate classification of the sensor and actuator fault types.

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