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RESEARCH ARTICLE

A Novel Dual Attention Convolutional Neural Network Based on Multisensory Frequency Features for Unmanned Aerial Vehicle Rotor Fault Diagnosis

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ABSTRACT By virtue of their convenience, reasonable cost and high efficiency, Unmanned Aerial Vehicles (UAVs) have been widely applied in every aspect of life. However, complicated operating conditions are prone to causing mechanical failure in UAVs, especially the rotor fault. Therefore, a novel dual attention convolutional neural network based on multisensory frequency features is proposed for UAV rotor fault diagnosis in this study. Firstly, according to the collected multisensory acceleration vibration signals of UAV rotors, time and frequency features in different health states (normal, rotor broken and crack fault) are compared and analyzed in detail. Secondly, a novel dual attention mechanism is proposed to not only focus on the effect of different sensors but also different frequency features of UAV. Moreover, it could adaptively assign larger weight to more important features to improve the fault diagnosis accuracy. Finally, a one-dimension convolutional neural network is adopted to extract the feature of signals and implement rotor fault diagnosis of UAV. The results derived from experimental signals demonstrate the superiority of the proposed method by comparison study. Additionally, it is found that the fault diagnosis accuracy of frequency features as input is much higher than that of time features and single frequency features as input.

INDEX TERMS Attention mechanism, convolutional neural network, rotor fault diagnosis, unmanned aerial vehicle.

I. INTRODUCTION

With the continuous evolution of modern technology, Unmanned Aerial Vehicles (UAVs) have been widely applied in every walk of life, such as aerial photography, cargo transportation as well as agricultural planting [1], [2]. The simple and effective structure of UAVs enables them to complete varieties of missions in complicated operation conditions. For example, hovering over a target at the set speed or avoiding obstacles and then performing complex maneuvers [3]. At the same time, when UAVs continuously replace humans to perform some difficult or even dangerous missions, their own components will also suffer from certain fatigue damage, which will further affect the reliability of their operation. Therefore, it is highly necessary to research fault diagnosis of UAVs to ensure their reliability during the flight and increase their remaining useful life.

Generally, the whole UAV system consists of many components, which can be briefly divided into the following parts: sensors, actuators, wireless system and microcomputer

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system [4]. In terms of fault diagnosis of UAVs, most of the existing studies focus on the sensors and the actuators in the flight system, while there are relatively few studies on other functional components, such as the rotor of UAVs [5]. For the failure of UAV sensors, the hardware redundancy method is adopted at the beginning. However, this method requires the system to be operated in triple or quadruple redundancy configurations and increases the cost and weight of the UAVs [6]. Afterwards, the residual evaluation method is proposed to detect UAVs sensor fault, which computes the residual information obtained from the difference between the output and the estimation and then completes sensor fault diagnosis [7]. Due to the potential to process the intelligent diagnosis through big data, the deep learning algorithm is gradually applied in sensor fault diagnosis. Olyaei et al. introduced Color Images obtained from Time-Frequency-Amplitude (CITFA) to complete sensor fault classification, which finally achieves the classification accuracy of 98% in simulations [8]. For the diagnosis of actuators, Lijia et al. combined robust adaptive observer and a Radial Basis Function Neural Network (RBFNN) to detect the ailerons, elevators and rudder fault of UAVs [9]. Zhong et al. developed an adaptive three state Kalman filter to not only detect the propeller and motor fault of UAVs but also evaluate their magnitudes [10]. Hansen et al. proposed a methodology using data from a swarm of UAVs to diagnose faults in both control surfaces and air system sensors [11]. In [12], the authors proposed a sliding mode observer for rotor fault diagnosis of UAVs, which calculates the equivalent uncertain inputs by the features of the outputs. As an important mechanical transmission component of UAVs, rotors support a large number of takeoffs, hover, elevation and yaw missions. Considering there are few literatures on rotor crack and broken fault diagnosis, it is necessary to conduct in-depth research on the above aspects.

In the field of fault diagnosis, the frequently used fault diagnosis methods can be generally divided into the following three categories: knowledge-based method, model-based method as well as data-driven method [13], [14], [15]. These methods are also applicable to the fault diagnosis of UAV. Knowledge-based methods primarily apply expertise to the UAVs diagnostic procedure. Aiming at the complexity, diversity and nonlinear mode of UAV measurement and control system faults, Xiao et al. proposed a modified expert system by combining neural network to improve the active learning ability of the traditional expert system [16]. Çolak et al. proposed a novel two phase multi expert knowledge approach by using fuzzy clustering and rule-based system to evaluate UAVs [17]. Model-based methods mainly construct physical model to estimate the state of UAVs and further diagnose the fault. Hansen et al. completed fault diagnosis of UAV airspeed measurement system based on extended Kalman filter (EKF) [18]. Wu et al. established a dynamic model with augmented state containing both the flight state and actuator healthy coefficients, and applied unscented Kalman filter to estimate the health state of UAVs [19]. Tousi et al. constructed

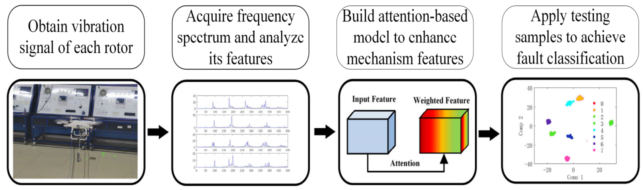

FIGURE 1. Brief flow chart of the proposed method.

the fault diagnosis scheme based on different components fault model of UAVs, which takes advantage of the structural perturbation of the UAV model due to the icing, sensor and actuator faults [20]. Due to their powerful data processing ability, data-driven methods directly construct the nonlinear relationship between operation data and equipment health status. Cabahug et al. used k-means clustering algorithm to fuse the vibration data and then detected midflight UAV failures [21]. In [22], the authors presented a novel data-driven adaptive neuron fuzzy inference system-based approach for the detection of navigation sensor faults in UAVs. Du et al. proposed an interval sampling reconstruction method for vibration signals and applied convolutional neural network to further extract the fault features of UAVs, the effectiveness of the method verified by the rotary-wing UAVs signals [23]. In sum, model-based methods are the most widely used, such as various types of Kalman filters, while data-driven methods based on artificial intelligence algorithms are relatively rarely applied in UAVs fault diagnosis. Additionally, how to build an appropriate intelligent diagnosis model according to the fault mechanism features of UAV signals is also a crucial topic.

As a result, a novel dual attention convolutional neural network based on fault frequency features is proposed for rotor fault diagnosis of UAVs in this paper. A brief flow chart of the proposed method is presented in Fig. 1. Firstly, according to the obtained vibration signals of each rotor, time and frequency features in different health states are detailed compared and analyzed from the flight principle of UAV. Secondly, based on the analysis of frequency features, a dual attention based convolutional neural network is built for intelligent diagnosis. Finally, the effectiveness and superiority of the proposed method are verified by the experimental signals from rotary-wing UAV. Additionally, several comparison studies are also conducted to show the advantage of the proposed method in detail. The main contributions and innovations of this paper are summarized as follows.

1) A comprehensive analysis of the frequency features of vibration acceleration signals from each rotor of the quadrotor UAV in different health states (normal, rotor broken, and crack fault) to unveil the corresponding fault mechanisms. Additionally, an explanation is provided for the occurrence of fault frequency features based on the flight principles of UAVs.
2) A novel dual attention convolutional neural network is proposed for rotor diagnosis of UAV, whose input are the multisensory frequency features with certain fault mechanism information. The proposed dual attention

module can not only adaptively assign great weight to important sensor signals, but also help the proposed network to center on the more essential frequency that represents the fault features. Experimental signals from quadrotor UAV are used to validate the method's effectiveness, and a comparison study demonstrates its superiority over other approaches.

The rest of this paper is organized as follows. Section II presents the preliminaries, including convolutional neural network and convolutional block attention module. Section III introduces the proposed network for rotor diagnosis. The experimental setup, frequency features analysis, validation and comparisons are considered in Section IV. Finally, Section V summarizes the conclusions.

II. PRELIMINARIES

A. CONVOLUTIONAL NEURAL NETWORK

Due to its powerful feature extraction ability, convolutional neural network (CNN) is widely applied in many fields, such as image classification, speech recognition and fault diagnosis. Typically, CNN contains several convolutional layers, pooling layers and fully connected layers in the end [24]. Compared with traditional fully connected network, CNN utilizes convolution kernel in convolutional layers to automatically extract abstract features from former layers, which leverages the local receptive ability so that it reduces the number of parameters and the training difficulty of the model.

Since the signals collected from acceleration vibration sensor are one-dimension time series instead of two-dimension image features, one-dimension CNN (1D-CNN) is chosen in this paper for network construction. In convolutional layer, convolution kernel is utilized to carry out convolution operation with signals to extract representative features. The formula of convolutional layers is defined as

$$x_j^l = f(\sum_i x_i^{l-1} * k_{ij}^l + b_j^l) \tag{1}$$

where x_i^{l-1} and x_j^l are the output feature of the layer $l-1$ and l respectively; f stands for the nonlinear activation function, ReLu is used as the activation function in this paper; $*$ means the convolution operator; k_{ij}^l is the convolution kernel of layer l, and b_j^l is the bias of layer l.

Pooling layer is usually connected behind convolutional layer to reduce the spatial dimension of the feature maps. Generally, pooling layer can be divided into two types: max pooling and average pooling. Max pooling operation adopts the maximum value in the pooling area and then propagates it to the next layer, while average pooling operation calculates the average value in the pooling area. The formula is represented as

$$x_j^{l+1} = \underset{i \in R_j}{\text{max or average}}(x_j^l) \tag{2}$$

where x_j^{l+1} and x_j^l are the output feature of the layer $l+1$ and l respectively; R_j is the j^{th} pooling region in the feature x_j^l.

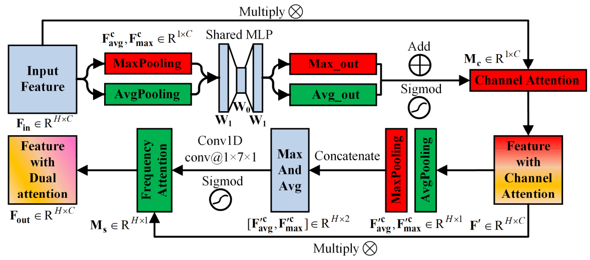

FIGURE 2. Network architecture of the dual-attention-based convolutional neural network.

B. CONVOLUTIONAL BLOCK ATTENTION MODULE

In neural network, attention mechanism could enhance some parts of the input data while diminishing other parts to help the network achieve better results. Traditional attention based intelligent diagnosis only pay attention to a single factor, such as temporal or sensor. Convolutional block attention module (CBAM) is first proposed in image classification to both focus on channel and temporal feature [25].

CBAM contains two submodules: channel and temporal attention modules. The first and second parts are to allocate different weights on different channel and temporal features, respectively. Supposing the input feature and output weighted feature are $\mathbf{F_{in}}, \mathbf{F_{out}} \in R^{H\times C}$, channel attention feature $\mathbf{M_c} \in R^{1\times C}$ and temporal attention feature $\mathbf{M_s} \in R^{H\times 1}$. All the procedures then can be described as [25]

$$\begin{aligned} \mathbf{F}' &= \mathbf{M_c}(\mathbf{F_{in}}) \otimes \mathbf{F_{in}} \\ \mathbf{F_{out}} &= \mathbf{M_s}(\mathbf{F}') \otimes \mathbf{F}' \end{aligned} \tag{3}$$

where $\otimes$ denotes element-wise multiplication and $\mathbf{F}'$ stands for middle feature map. Specific attention module can be described in detail as

$$\mathbf{M_c}(\mathbf{F_{in}}) = \sigma(\mathbf{W_1}(\mathbf{W_0}(\mathbf{F_{avg}^c})) + \mathbf{W_1}(\mathbf{W_0}(\mathbf{F_{max}^c})) \tag{4}$$

$$\mathbf{M_s}(\mathbf{F}') = \sigma(f^{7\times 7}([\mathbf{F'^s_{avg}}; \mathbf{F'^s_{max}}])) \tag{5}$$

where σ stands for the sigmoid function, $\mathbf{W_0}$ and $\mathbf{W_1}$ are the weights of the two fully connected layers, $\mathbf{F_{avg}^c}$ and $\mathbf{F_{max}^c}$ denote features after average and max pooling respectively, $f^{7\times 7}$ represents convolution operation of 7×7 convolution kernel. It should be noticed that the original CBAM in [25] deals with two-dimension data, such as images, but in this paper, the attention network structure has been slightly changed to make it suitable for dealing with one-dimension data, such as vibration signals. The specific network structure of the modified CBAM is presented in Fig. 2.

C. DYNAMICS ANALYSIS OF UAV

When the rotor is damaged, the force of the UAV may be unbalanced, resulting in shaking or even falling. Therefore, the rotor failure will have a huge impact on the flight stability of the UAV. Considering the UAV as a rigid body, the six degrees of freedom in flight are described by three linear motions of the center of mass of the body that translate along the coordinate axis and three angular motions that rotate around the coordinate axis.

$$F = m\dot{V} = m[\ddot{x} \quad \ddot{y} \quad \ddot{z}] \tag{6}$$

$$M = I\dot{W} + W \times (IW) \tag{7}$$

where F represents the total external force on the drone, m is the mass of the UAV, V is the linear velocity of the center of mass of the drone. x, y and z represent the position information in space, respectively. $\ddot{x}$, $\ddot{y}$ and $\ddot{z}$ represent the unmanned the linear acceleration component of the drone's center of mass along the three-axis direction. M is the resultant external torque received by the rigid body, I is the inertia matrix, and W is the angular velocity of the rigid body.

III. PROPOSED METHOD

The proposed method for UAV rotor fault diagnosis mainly consists of the following two steps: 1) multisensory frequency features input construction; 2) dual-attention-based convolutional neural network construction and implementation.

A. MULTISENSORY FREQUENCY FEATURES INPUT CONSTRUCTION

Due to the influence of environmental noise and signals generated by other components, it is difficult to utilize the vibration signals in time domain to achieve rotor fault diagnosis of UAV. Since UAV rotor is rotating part, its vibration signal features are mainly related to the rotation frequency of rotors. It is reasonable to convert vibration signals from time domain to frequency domain by Fourier transform. In this way, the features signal representing health states of UAV rotor could be highlighted in frequency domain. Additionally, UAV contains multiple rotors, utilizing multiple sensors to acquire vibration signals of each rotor can more accurately determine its health states. Therefore, multisensory frequency features of UAV rotor are used as input to train and test the proposed network. The specific construction method is as follows:

1) In order to increase the number of data samples, the time domain vibration signals of each rotor $x_i(t)$ are firstly processed by sliding window method. Window length is set as 4096, which is enough for generating lots of samples. Signal length of each sample is 16384, which will be discussed in experimental results.
2) Applying Fourier transform to convert the time domain vibration signals of each rotor $x_i(t)$ into frequency domain $X_i(f)$ by the following equation. Since the spectrum of the signal is symmetric, only half the length of $X_i(f)$ is selected as input.

$$X_i(f) = F[x_i(t)] = \int_{-\infty}^{\infty} x_i(t) e^{-j2\pi ft} dt \tag{8}$$

where j represents for imaginary unit; F stands for Fourier transform; $x_i(t)$ and $X_i(f)$ are the time and frequency domain vibration signal under the i^{th} rotor, respectively.
3) The frequency domain signals of all the rotors $X_i(f)$ are formed into a matrix $\mathbf{X}$ as the input of the proposed neural network. $\mathbf{X} = [X_1(f); X_2(f); \ldots; X_C(f)]^T$, $\mathbf{X} \in \mathrm{R}^{H \times C}$ is frequency domain signals length, which is 8192, and C is number of rotors which equals to 4 in this paper.

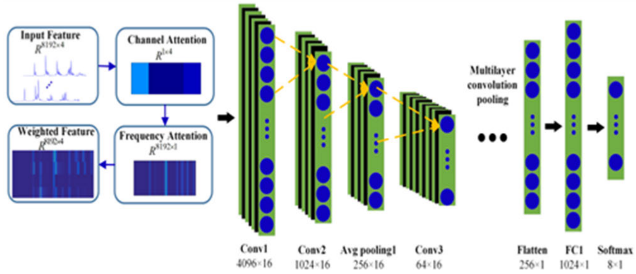

FIGURE 3. Network architecture of the proposed method.

TABLE 1. Network parameters of the proposed model.

Module	Layer	Parameter
Input (N, 8192, 4)	-	-
CBAM (N, 8192, 4)	Channel Attention	-
	Multiply	-
	Spatial Attention	-
	Multiply	-
1D Convolution (N, 8, 32)	Convolution1	conv@16×64×2conv@
	Convolution2+BN	16×64×4
	AveragePooling1	avgp@8×4
	Convolution3+BN	conv@32×128×4
	Convolution4+BN	conv@32×128×4
	AveragePooling2	avgp@2×2
Flatten (N, 256)	Flatten	-
Dense (N, 8)	Dense1+Dropout(0.5)	1024(ReLu)
	Dense2	8(Softmax)

B. NETWORK ARCHITECTURE AND IMPLEMENTATION

The proposed dual-attention-based convolutional neural network for UAV rotor fault diagnosis is illustrated in Fig. 3. It can be roughly divided into three modules: 1) dual attention convolution module; 2) 1D convolution feature extraction module; 3) fully connected classification module. Network parameters of the proposed model are listed in Table 1. Detailed process of the proposed method is summarized as follows:

1) According to the introduction of Section III, multisensory frequency features input matrix $\mathrm{X} \in \mathrm{R}^{8192\times4}$ is constructed. In order to improve the fault diagnosis accuracy of network, CBAM is integrated into convolutional neural network to adaptively assign different weights on different sensors (channels) and frequency components. More importantly, through training the proposed network with samples, the dual attention mechanism can capture the difference between the

frequency features of healthy and different fault types of rotors, and then highlight the frequency components highly related with their health state, and suppress the influence of irrelevant frequency components. Since CABM only weighs the features of different dimensions of the input matrix, thus its dimension still remains unchanged (N, 8192, 4). N represents for the number of samples.

2) Then, 1D-CNN is placed after the weighted input frequency features. This module is to mine the abstract high-level features representing their health state by serval convolution and pooling operations. Specific network parameters of 1D-CNN are listed in Table 1. For example, conv@$16 \times 64 \times 2$ means applying 16 filters with kernel size 64 and strides 2, avgp@8×4 stands for applying average pooling with pooling size 8 and strides 2. To avoid overfitting, batch normalization (BN) is also adopted in the proposed network. By means of multilayer convolution and pooling operations, the dimension of features becomes (N, 8, 32). Moreover, Advanced Data Access Method is the method used for parameter updating at each layer. The specific optimization process is as follows:
Update the first moment estimate m and the second moment estimate v:

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t \tag{9}$$
$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2 \tag{10}$$

where β_1 and β_2 are the hyper-parameter, they are generally set to 0.9 and 0.999, respectively, t is the number of iterations.
Since the initial estimates of m and v are 0, they will be biased at the beginning of training. In order to correct this bias, bias correction is required:

$$m_t' = m_t/(1 - \beta_1^t) \tag{11}$$
$$v_t' = v_t/(1 - \beta_2^t) \tag{12}$$

The modified first and second moment estimates were used to update the model parameters w:

$$w_{t+1} = w_t - l \times m_t'/(\sqrt{v_t'} + e) \tag{13}$$

where l stands for the learning rate and set to 0.001, $e$indicates the smooth item, which is usually set to 1×10^{-8}.

3) Finally, one Flatten and two Dense layers are sequentially connected together to achieve rotor fault diagnosis. The first Dense layer utilizes ReLu activation function, while the second Dense layer applies Softmax classifier for multi-classification. Additionally, Dropout method is also adopted to avoid overfitting. Corresponding steps of the algorithm is summarized in Algorithm 1.

Algorithm 1 Pseudo-Code of the Proposed Model

Multisensory Frequency Features Input Construction
1: Collect all four rotor vibration acceleration signals in time domain $x_i(t)$
2: Apply FFT transformation to obtain frequency signals $X_i(f)$
3: Construct the input matrix X=[$X_1(f)$; $X_2(f)$; $X_3(f)$; $X_4(f)$]$^{\mathrm{T}}$
Training and Test Procedures of the Proposed Model
Input: The labeled dataset D = {($\mathbf{X}_1$,$\mathbf{Y}_1$), ($\mathbf{X}_2$,$\mathbf{Y}_2$), ..., (X_M,Y_M)}
1: Set model hyperparameters such as learning rate, iteration number and batch size
2: Randomly initialize the weights and biases of the model
3: Divide the training and test datasets
4: **For** each training epoch **do**
5: **If** phase = train **then**
6: **For** each data batch **do**
7: Calculate the output of the proposed model
8: Update weight parameters of the proposed model
9: **End For**
10: **If** phase = test **then**
11: Calculate the output of the proposed model
12: **End For**
Output: Fault classification results on the test set

(a) (b) (c)

FIGURE 4. Experimental test system. (a) Quadrotor UAV; (b) Name of each rotor; (c) Vibration signal acquisition system.

IV. EXPERIMENTAL VERIFICATION

A. UAV ROTOR FAULT EXPERIMENTAL SETUP

To verify the effectiveness of the proposed neural network on UAV rotor fault diagnosis, the experiment was conducted on a China DJI Series Phantom 4Pro+ V20 quadrotor UAV, four printed circuit board acceleration vibration sensors were mounted on each rotor to collect multisensory signals, rotors are named as a, b c, and d, respectively, as shown in Fig. 4(a) and (b). ECNO AVANT series data acquisition analyzer and laptops were combined together to analyze the signals, as shown in Fig. 4(c). The sampling frequency was set to 12800 Hz, sampling time for each experiment was nearly 35 s.

In UAV rotor experiment, three types of rotor failure state were manually set: normal state, rotor broken fault as well as rotor crack fault, as presented in Fig. 5. In normal state, all the rotors are in health without damage; In rotor broken state, there are three levels of damage: minor (both ends of the rotor c were cut slightly), moderate (one end of the rotor c was cut slightly, while the other end was cut considerably) and severe (both ends of the rotor c were cut considerably); In rotor crack state, there are four levels of damage: one 1 cm crack on the rotor c, two 1 cm cracks on two opposite rotors b and c, four 1 cm cracks on two opposite rotors b and c, six 1 cm cracks on the rotor c. The number of the rotor faults are labeled from 0 to 7 in order. During the experiment, UAV was

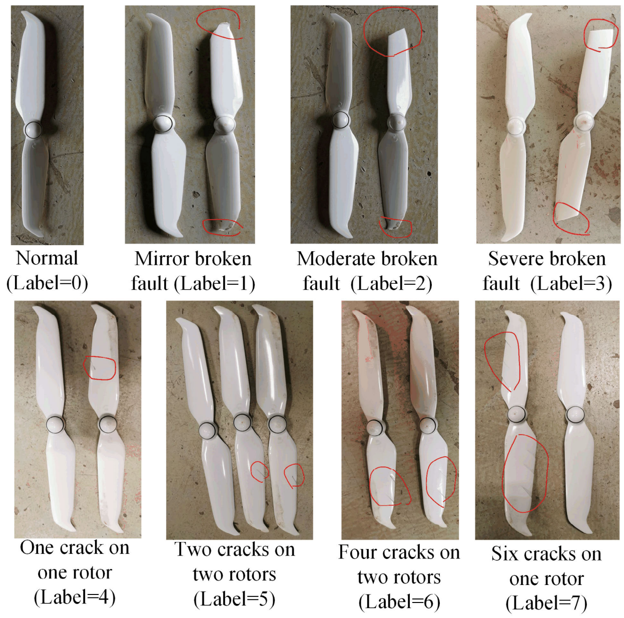

FIGURE 5. Normal rotor, broken and crack rotor with different fault levels.

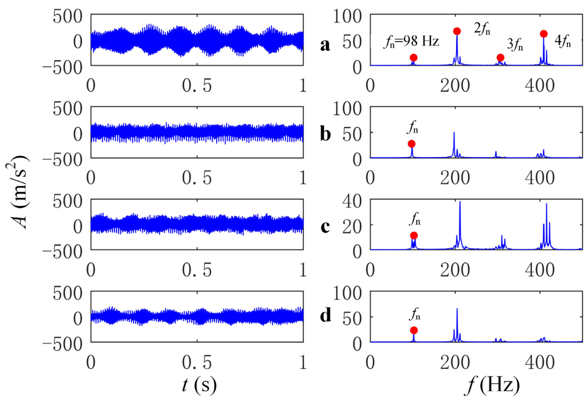

FIGURE 6. UAV Rotor vibration signals of time and frequency domain in normal state.

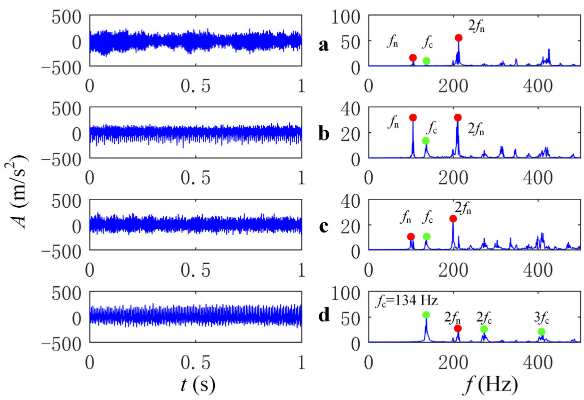

FIGURE 7. UAV Rotor vibration signals of time and frequency domain in severe broken fault.

hovering at an altitude of 2 m controlled by DJI remote, this process involved hovering, taking off and turning. A total of eight datasets can be acquired under these three types of rotor failure state.

B. MULTISENSORY FREQUENCY FEATURES ANALYSIS

Compared with the traditional single sensor method, multiple sensors mounted on each rotor can obtain more accurate information representing their health condition. Additionally, multisensory frequency features of UAV rotor in health and fault states are not clear. Therefore, the analysis of multisensory frequency features of UAV rotor is helpful for rotor fault diagnosis. According to UAV rotor fault experiments, multisensory acceleration vibration signals of rotors in different health states are collected. Taking normal state, severe rotor broken fault and six cracks on one rotor fault as examples, the multisensory frequency features of UAV rotors are analyzed in detail.

In normal state, UAV rotor multisensory vibration signals of time and frequency domain are illustrated in Fig. 6. Firstly, it is difficult to directly observe their running state from time domain, the time domain signals of all rotors do not exist any features; Secondly, all frequency domain signals include rotational frequency of rotor ($f_n = 98$ Hz) and its harmonic components, furthermore, due to the inevitable presence of the rotor speed fluctuations, there is a certain frequency aliasing phenomenon near the rotational frequency and its harmonic components. In sum, acceleration vibration signals of different rotors (rotor a, b, c and d) basically have similar features in time and frequency domain, which are in line with the flight principle of UAV during hovering (four rotors rotate at the same speed, and the sum of the lift generated by rotors equals to their own gravity).

In severe rotor broken fault, UAV rotor multisensory vibration signals of time and frequency domain are presented in Fig. 7. Similar to the normal state, it is still hard to obtain the information characterizing rotor fault features in time domain directly. In contrast, the frequency domain signal features of each rotor are very obvious. In addition to rotational frequency of rotor ($f_n = 98$ Hz) and its harmonic components contained in the normal state, the fault characteristic frequency ($f_c = 134$ Hz) and its harmonic components also appear in severe rotor broken fault. Furthermore, all rotor signals, whether healthy (rotor a, b and d) or faulty (rotor c), exhibit the above frequency features. It is worth noting that compared with the signal of faulty rotor c, the signal features ($f_c = 134$ Hz) of the adjacent healthy rotor d are more obvious. This is mainly because when rotor c occurs broken fault, its rotational speed would change, resulting in additional frequency component ($f_c = 134$ Hz) in frequency domain. In order to keep UAV hovering and balance the lift generated by faulty rotor, the rest rotors rotational speed will also change accordingly and generate fault characteristic frequency.

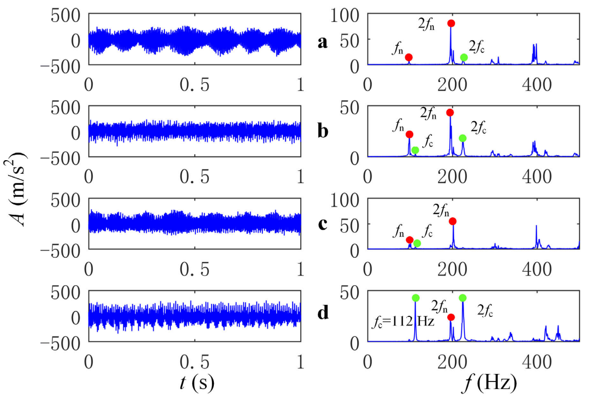

FIGURE 8. UAV Rotor vibration signals of time and frequency domain in six cracks on one rotor.

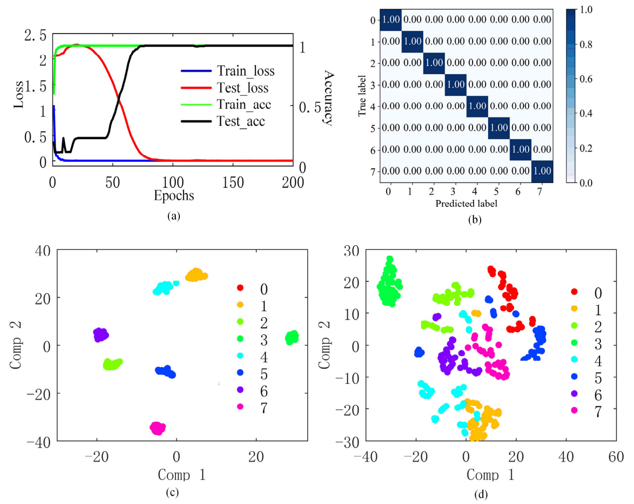

FIGURE 9. The classification and t-SNE results by the proposed method. (a) Loss and accuracy curve; (b) Confusion matrix; (c) t-SNE of Input layer; (d) t-SNE of Dense layer.

In six cracks on one rotor fault, multisensory frequency features are similar to the rotor broken fault, as shown in Fig. 8. Both rotational frequency ($f_n = 98$ Hz) and fault characteristic frequency ($f_c = 112$ Hz) are appeared in frequency domain. However, due to the different types and levels of fault, the value of the fault characteristic frequency is different from the rotor broken fault.

In summary, whether the rotor is normal or faulty, it is difficult to directly observe any features from time domain. On the contrary, frequency features of rotors are obvious in normal and faulty state, and due to the existence of fault characteristic frequency, there are certain differences under different states, which can be further utilized for diagnosis.

C. EXPERIMENTAL RESULTS

Acceleration vibration signals of UAV rotors with eight different fault levels are acquired by experiments, and fault classification are performed by the proposed dual-attention-based 1D-CNN method. The computer system used to process the data is windows 10 with 16G RAM and NVIDIA GeForce GTX 1050 Ti, the configured environment is python 3.6, tensorflow-gpu 2.1.0.

Firstly, according to Section III, multisensory frequency features input matrix $X \in R^{8192\times 4}$ is constructed. The ratio of number of samples in training set and testing set is 6:4. Adam optimization algorithm is applied to adaptively calculate the learning rate. Initial learning rate, batch size and epoch are set as 0.001, 64 and 200, respectively. The proposed method contains 488749 trainable parameters and 160 non-trainable parameters, respectively. Then, utilizing training sets to train the proposed network so as to obtain the optimal network model parameters. Finally, testing sets are input into the trained network to achieve fault diagnosis. Total running time of the proposed model equals to 55.41 seconds, which is enough fast for practical UAV rotor fault diagnosis.

The evolution of several parameters of the proposed CNN model have been illustrated during the learning phase (training phase). From Fig. 9(a), it can be seen that the loss of training sets and testing sets both decrease to 0 without fluctuation after 200 iterations. Meanwhile, the accuracy of training sets and testing sets are both approximately close to 1. These two types of curves indicate that the proposed network with multisensory frequency features could well achieve fault diagnosis of UAV rotor. Moreover, to show the classification results of various rotor faults more intuitively, a confusion matrix is illustrated in Fig. 9(b). The prediction accuracy of each rotor fault type reaches to 1, which further demonstrate the effectiveness of the proposed method. In order to verify the feature extraction ability of the proposed method, the t-distributed Stochastic Neighbor Embedding (t-SNE) technique [23] is considered for visualization by mapping the high-level features in the Input layer and Dense layer into 2 dimensions, as presented in Fig. 9(c) and (d). From the visualization results, it can be clearly seen that most of the categories are overlapped with others in Input layer, though multisensory frequency features after dimensionality reduction could distinguish category 3. In contrast, the features derived from Dense layer, which have been already processed by several convolutional layers, are well clustered and all of the categories are separated with each other. Additionally, the evolutions of corresponding parameters of the dense layer (weights and biases) are also presented Fig. 10. As can be seen, the values of weights and biases basically tend to stable after 20 iterations, which keep consistent with the curve of accuracy and loss. The results show that the proposed network can learn meaningful discriminative features from the Input layer, which is helpful to yield high classification performance.

Furthermore, to illustrate the effectiveness of the modified CBAM (dual attention mechanism) integrated in the proposed network, both frequency and sensor attention values on all testing samples are plotted in Fig. 11. It can be seen that the modified CBAM can adaptively learn which frequency components and sensors (channels) in testing samples are more

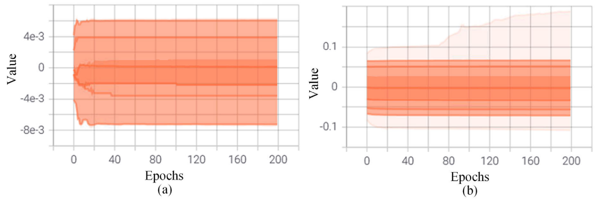

FIGURE 10. Evolution of the parameters during the learning phase: (a) weights of dense layer; (b) biases of dense layer.

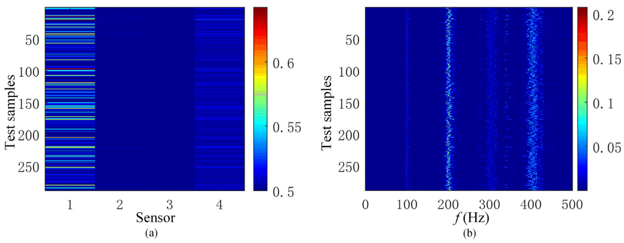

FIGURE 11. Attention values on all testing samples. (a) Sensor attention; (b) Frequency attention.

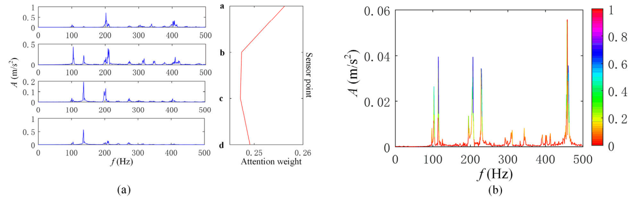

FIGURE 12. Attention weights visualization of one of the testing samples. (a) Visualization of sensor attention weights; (b) Visualization of the learned attention weights on single rotor frequency features.

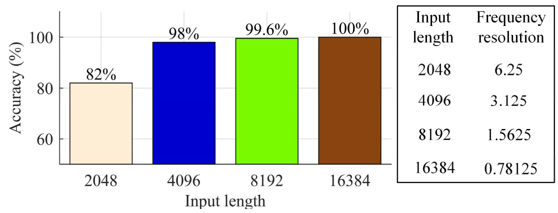

FIGURE 13. The classification accuracy under different signal input length (frequency resolution).

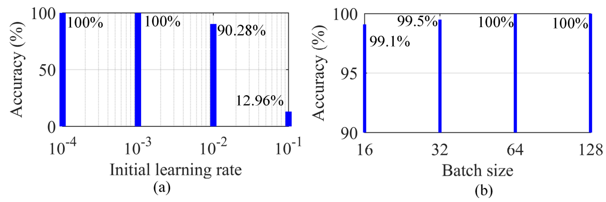

FIGURE 14. The classification accuracy: (a) different initial learning rates; (b) different batch sizes.

important for fault classification. Specifically, the weights of sensor attention are also different under different testing samples; In addition, the weights of frequency attention distributed in the vicinity of rotational frequency (f_n), characteristic frequency (f_c) and its harmonics are larger than that of the other frequency components. These two results directly demonstrate that the modified CBAM can adaptively assign different weights on different frequencies and sensors by network training.

To explain the distribution of attention weight more intuitively, both sensor attention and frequency attention weights of one of the testing samples are presented in Fig. 12. According to multisensory frequency features analysis of UAV rotors in multisensory frequency features analysis, signal frequency features of each rotor will be different under fault condition, especially in fault characteristic frequency (f_c). Therefore, the proposed attention mechanism could adaptively assign different weights to the different sensors, as shown in Fig. 12(a). In terms of single rotor frequency attention, it can be clearly found that larger weights with dark color are assigned near rotational frequency (f_n), characteristic frequency (f_c) and its harmonics from Fig. 12(b). These features with larger attention weights are highly corelated to UAV rotors health, which also verifies the effectiveness of the proposed attention mechanism.

Based on sliding window method to expand the number of samples, the shorter signal length, the greater number of samples, which is beneficial for network training. While from the perspective of signal processing, the longer signal length in time domain, the higher frequency resolution of the signal in frequency domain, and the more accurate frequency features of the signal can be analyzed, which is conducive to fault diagnosis. Hence, signal length of samples not only determine the number of samples, but also determine the information contained in the samples. In order to balance these two factors, different signal lengths are set to study their influence on the final classification accuracy. As illustrated in Fig. 13, when the signal length is 2048, the fault classification accuracy only equals to 82%, mainly due to low frequency resolution (6.25 Hz) is not enough to detect the feature frequency. As the length of signal increases, the classification accuracy reaches to 100% with high frequency resolution 0.78 Hz. Therefore, signal length is chosen as 16384 in this paper.

Moreover, the classification results of different values of initial learning rate and batch size are plotted in Fig. 14. As we know, the lower learning rate, the higher classification accuracy will be, but the training time will increase, hence in order to balance the training time and accuracy, initial learning rate is set as 0.001. Batch size is selected as 64 by the same logic.

D. COMPARISON STUDY

In this section, several machine learning algorithms are compared with the proposed method to verify its superiority. Especially, to avoid random error, all the methods are conducted five times to record average fault classification accuracy.

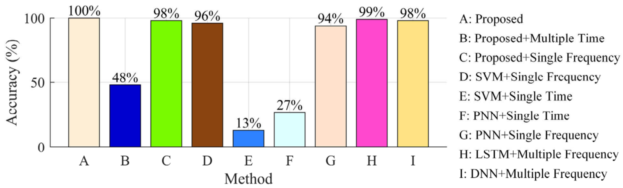

FIGURE 15. Classification accuracy results of different methods.

A total of nine methods are compared: the proposed method is labeled as A, the proposed method utilizing multiple time as input and single frequency as input are labeled as B and C, respectively. Support vector machine (SVM) applies single frequency and single time as input are labeled as D and E, respectively. Probabilistic neural network (PNN) uses single time and single frequency as input are labeled as F and G, respectively. For SVM method, grid searching technique is applied to select the optimal parameters of c, gamma and kernel, whose search range are [0.1,1, 10, 100], [1,0.1,0.01,0.001] and ['rbf', 'poly', 'sigmoid']. Then, the optimal parameters are selected with [c = 100, gamma = 0.1, kernel = 'rbf'] and [c = 0.1, gamma = 1, kernel = 'poly'] in method D and E. For PNN method, the std parameter also is determined by grid searching technique, whose optimal value is 30 and 0.2 in method F and G. Stack LSTM network and DNN network with multiple frequency as input are labeled as E and I.

According to the comparison results from Fig. 15, the following conclusions can be derived: (1) the proposed method achieves 100% classification accuracy, which is the highest among all of the comparison methods; (2) compared with method H and I, the accuracy of the proposed is also slightly higher than that of popular LSTM and DNN (100% vs 99% and 98%); (3) by comparing the method A and B, D and E, F and G separately, it could be found that the method utilizes frequency as input have much higher accuracy than that of using time as input (100% vs 48%, 96% vs 13% and 94% vs 27%); (4) through the comparison of A and C, it can be known that using multisensory frequency features as input could improve the fault classification accuracy from 98% to 100%. In sum, the comparison results not only demonstrate the superiority of the proposed method in UAV rotor fault diagnosis, but also verify the effectiveness of applying multisensory frequency features as input.

To further illustrate the advantage of using multisensory frequency features, the classification and t-SNE results by taking time domain signals as input are presented. As can be seen in Fig. 16(a) and (b), although the loss of training sets is close to 0, the loss of testing sets still cannot converge to 0 after 200 iterations. It can also be clearly seen from the confusion matrix that this method is difficult to discriminate different fault labels of UAV rotors accurately and has relatively poor generalization ability. Furthermore, from the visualization results in Fig. 16(c) and (d), it can be known that all categories of time feature in Input layer are

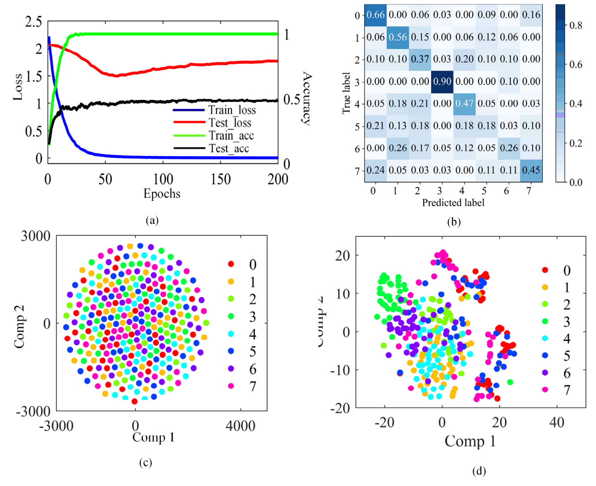

FIGURE 16. The classification and t-SNE results by taking time domain signals as input. (a) Loss and accuracy curve; (b) Confusion matrix; (c) t-SNE of Input layer; (d) t-SNE of Dense layer.

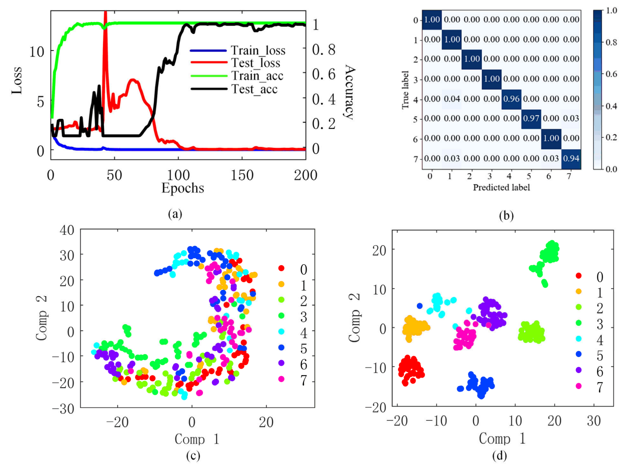

FIGURE 17. The classification and t-SNE results by taking single frequency signals as input. (a) Loss and accuracy curve; (b) Confusion matrix; (c) t-SNE of Input layer; (d) t-SNE of Dense layer.

heavily overlapped with each other by t-SNE, the features of same category in Dense layer form certain clusters, but there still exists large feature overlap phenomenon. By comparing the results in Fig. 9(c) and (d), it is easy to know that using frequency features as input is more reliable than using time features for UAV rotor's fault diagnosis.

Similarly, the classification and t-SNE results of applying single frequency feature as input are plotted in Fig. 17. The loss and accuracy curve and confusion matrix together show its effectiveness of UAV rotor fault diagnosis. However, comparing with the results in Fig. 9(a) and (b), this method not only requires more epochs to achieve convergence but also generates some fault classification errors (Fault label 4, 5, and 7). Hence, in order to keep the parameters consistent with other comparison methods, the iteration number (epoch) is set as 200 in all methods. Additionally, t-SNE results of Input and Densen layer intuitively demonstrate the clustering ability, but it is still inferior to the proposed method utilizing multisensory frequency features as input as shown in Fig. 17(c) and (d).

V. CONCLUSION

This paper proposes a novel dual attention convolutional neural network based on multisensory frequency features to achieve UAVs rotor fault diagnosis. Firstly, according to the collected multisensory acceleration vibration signals of UAV rotors, both time and frequency features are compared and analyzed in accordance with flight principle of UAV in detail. It can be known that utilizing characteristic frequency (f_c) of multisensory signals can well indicate the fault types of UAV rotors, while the time features of multisensory signals cannot. Then, a modified CBAM is integrated into the network to implement the dual attention weighting (both sensor and frequency) of signal. Through dual attention mechanism, larger weights can be adaptively assigned to sensors and frequency components that better characterize the health of UAV rotors. Finally, a 1D-CNN is adopted to extract the feature of signals and implement rotor fault diagnosis of UAV.

The experimental results indicate that the proposed method could accurately discriminate various fault types of UAV rotors (health, three different levels of broken fault and four different levels of crack fault). Moreover, larger attention weights are located at important sensor signal and frequency components (rotational frequency, characteristic frequency and its harmonics). In comparison study, the proposed method achieves 100% fault classification accuracy, which is highest among SVM, PNN, LSTM and DNN. Additionally, the proposed method applies multisensory frequency features as input could improve the fault classification accuracy from 48% and 98% to 100% by comparing with applying multisensory time features and single frequency features as input.

During the flight of UAVs, in addition to constant speed hovering mission, there are more rapid climbing and landing missions, which will inevitably generate variable speed and lead to more complicate task for accurate fault diagnosis of UAV rotors. Hence, in the future fault diagnosis method of UAV rotors under variable speed condition will be further studied on the basic of existing research.

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