

Real-time edge computing system for crack detection of UAV structures

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Abstract—In this research, a real-time detection system for UAV structural cracks based on edge computing technology was proposed, aiming to improve the detection efficiency and flight safety. The system uses a 1D Convolutional Neural Network (1D-CNN) deep learning model running on a microcontroller platform to automatically extract features from vibration data and make real-time inferences without cloud computing. Compared with the traditional server-dependent fault diagnosis method, this method reduces the computing delay and network transmission pressure, and the experimental results achieves 98% detection accuracy on resource-constrained equipment, which effectively guarantees the operation safety of the UAV.

This achievement can be directly deployed on the miniature hardware of the UAV to demonstrate convenience, low power consumption and high performance. Although faced with the limitations of memory and computing capability, this research successfully challenges by quantifying the model and optimizing the hardware design, providing a universal and scalable solution for UAV safety detection technology.

Keywords—real-time, crack, edge computing, vibration, detection.

I. INTRODUCTION

Due to the flexibility and versatility, UAVs have been widely used in many industries and shown great economic and social value. But, its high frequency of use and working principle also leads to the risks when structure fail, posing a threat to the safety of personnel and property. For example, during the 2015 International Ski Federation Alpine Skiing Competition, a UAV crashed because structural failure and nearly hit a participant; In 2016, at a mass event in Quebec, Canada, a UAV fell out of control, injuring several participants. These events highlight the importance of real-time detection of UAV structures, especially cracks, which are nearly invisible but potentially dangerous faults.

Traditional UAV structure inspection methods often rely on manual inspection, or server processing based on high computing resources. However, manual inspection is not only costly and inefficient, but also difficult to accurately detect early

faults such as cracks. Although instrument testing can provide more accurate data, it is difficult to promote it on a large scale owing to the cost of equipment and the need for professional operation. The following traditional methods present many practical and cost-effective challenges:

- Visual inspection: usually carried out by experienced technicians, relying on the naked eye or the assistance of magnifying glasses, microscopes and other equipment. However, this method is inefficient and susceptible to subjective judgment. In addition to being ineffective for hidden areas. Also, varies depending on the level of expertise. Estimated to be around \$20-50 for one person per hour.
- Ultrasonic Testing (UT): Use ultrasonic detectors to conduct internal inspection of structures, and analyze the location and size of cracks through waveform echoes. Although this method can accurately detect internal structural problems, the instrument cost is high, about US\$5,000-20,000 per set. Besides, instrument operators require professional training. When labor and training costs are added, the detection threshold is further raised.
- Infrared Thermography (IRT): Use an infrared camera to measure surface temperature distribution changes to determine cracks and stress concentration locations. But, IRT has limited sensitivity to the depth and position of cracks, and is also affected by changes in environmental conditions such as light and temperature. The equipment price alone is approximately US\$3,000-10,000.
- Magnetic Particle Testing (MPT): Detects cracks on metal surfaces through magnetic fields and magnetic particles, suitable for inspecting structural problems of metal UAVs. However, this method is not suitable for detecting non-metallic materials, for instance plastics and composite types. Moreover, the operation requires experienced operators, and cost is about US\$1,000-5,000.
- Flight Data Analysis (FDA): Use the built-in recorder to analyze abnormal situations through vibration signals and operating data. However, the FDA cannot detect fine

cracks, and data analysis still relies on high computing resources and professional algorithms. Although the cost is relatively low, high-performance analysis tools may require expensive software and hardware equipment.

These methods perform well in some specific applications, but suffer from various problems. Such as cost, low efficiency, high professional requirements, and even being limited to certain fields.

Due to the rapid development of deep learning technology, the research scope of structural inspection applied to UAVs has gradually increased. For example, in [1], a vibration signal based on interval sampling reconstruction is proposed, and a UAV rotor fault diagnosis method is combined with the 1D-CNN model, making the model perform excellent accuracy and stability in the classification of minor faults.

In [2], a lightweight fault detection system based on audio signals is demonstrated, proving the application potential of audio data in the detection of UAV structures. In [3], a hybrid model of CNN and LSTM was proposed for fault diagnosis of six-rotor UAVs, emphasizing the role of time series data analysis in improving detection accuracy. A Bayesian deep learning network based on edge computing is proposed in [4], shows that distributed processing of edge devices can effectively reduce network load and improve immediacy.

Explainable Artificial Intelligence (XAI) technology have also been applied in vibration data analysis. In [5], the XAI was combined to improve the interpretability of the deep learning model and acquired excellent performance.

II. TECHNICAL ANALYSIS

The application potential of deep learning technology in UAV structure detection was revealed in [1-5]. This research draws from these aspects:

- The 1D-CNN model is used for automated feature extraction of vibration signals. Thanks to [1], the edge computing efficiency of the model is improved to achieve instant detection.
- The contribution of [4] inspired this research to reduce computing resource through quantitative models to achieve efficient reasoning in edge computing.
- Inspired by [5] on multi-modal data fusion and model interpretability, this research plan combines vibration, sound data and explores XAI technology. In order to more accurately detect structural failures of UAVs.

A. Use of accelerometer

This research proposes to use accelerometers which can perform structural detection on UAVs in a cost-effective manner, then adapted to edge computing systems through lightweight design. An accelerometer is a device designed according to the law of inertial motion to measure changes in the acceleration of an object. The core in accelerometer consists of an internal inertial mass (Proof Mass) and a fixed structure. When external force is applied to the device, the inertial mass will be affected and resulting in displacement, thereby changing the equivalent capacitance or resistance. Eventually these changes will be

converted into voltages or even digital signals. In particular, capacitive accelerometers have the advantages of low power consumption, high sensitivity and miniaturization. With these advantages, capacitive accelerometers are very suitable for UAV structure detection. The reasons are listed as follows:

1. Sensitivity of vibration characteristics: Cracks in the structure will cause abnormal vibration characteristics, this in turn leads to changes in the frequency, amplitude and phase of the signal. With extremely high sensitivity, small changes can be captured more accurately, especially in early crack detection.

2. Low power consumption suitable for edge computing: Modern accelerometers not only have high sensitivity, but also have low power consumption, are suitable for use in resource-limited systems such as UAVs.

3. Versatility and data processing convenience: Modern accelerometers provide digital outputs, the interface seamlessly with embedded microcontrollers. The electrical interface greatly simplifies data transmission and system integration, facilitating real-time data processing under resource constraints.

4. Balance the cost and performance: Compared with UT and IRT, accelerometers are more cost-effective and appropriate than MPT for many modern UAVs those made by non-metallic materials.

This research plan to use 1kHz sampling rate, to record the three-axis acceleration. And uses sliding window technology to divide samples. In terms of feature selection, acceleration is used as the main feature, the angular velocity will be excluded.

Because the angular velocity mainly describes the rotational motion, it is used to detect the attitude and directional stability of the UAV. Therefore, as a manifestation of structural damage, cracks affect the transmission and attenuation of vibration signals. Weakly related to posture changes and movements. Using angular velocity data may introduce irrelevant features, leading to feature redundancy, which may put the model at risk of overfitting, or even affect the generalization ability of the model.

B. Using 1D-CNN for feature extraction

1D-CNN is a deep learning model for feature extraction of one-dimensional data, such as time series, vibration signals. The focus is to use convolution operations to extract local features of the inputs. In this way, 1D-CNN is more sensitive to the local characteristics of time series data. The key to describing the main operation process of 1D-CNN mathematically can be understood as follows:

The convolutional layers extract local features by applying convolution kernels (filters). Assume that the input X which data length is n , so $X \in R^n$, the length of the convolution kernel is k , so $W \in R^k$, then the output feature map Y should be represented by $Y \in R^{n-k+1}$, the operation formula is as shown in (1):

$$Y_i = \sum_{j=1}^k W_j X_{i+j-1} + b, i \in [1, n - k + 1] \quad (1)$$

Where b is the offset, and Y_i represents the output of the i -th convolution. The operations are performed in a sliding manner,

the number of parameters can be significantly reduced by sharing weights technique.

The nonlinear transformation of the convolution outputs is usually implemented using Rectified Linear Unit (ReLU), the formula shown in (2):

$$\text{ReLU}(z) = \max(0, z) \quad (2)$$

activation function introduces nonlinear capabilities, allowing the network to fit complex patterns.

The pooling layer performs dimensionality reduction on features to reduce the number of parameters and computational complexity. The most popular shall be max pooling, with the formula as (3):

$$P_i = \max_{j \in [1, p]} Y_{(i-1)p+j}, i \in \left[1, \frac{n}{p}\right] \quad (3)$$

Where p is the size of the pooling window, and P_i is the output after pooling. Then, the feature map is flattened into a one-dimensional vector through the fully connected layer. After that, classification or regression is performed. The formula is as shown in (4):

$$Z = W_f \cdot F + b_f \quad (4)$$

Where W_f is the weight matrix, F represents the flattened feature vector, and b_f is the offset.

C. Advantages of quantization technique

When the convolution kernel of 1D-CNN slides the data, parameter sharing prevents the number of weights in the model from increasing with the length of the inputs, this benefits extremely to resource-constrained context. If the floating-point numbers in the model (such as 32-bit floating-point numbers) can be compressed into integers with fixed memory space (such as 8-bit integers) through quantization technique, the memory usage and computing requirements can be greatly reduced. The equation of quantification is shown in (5):

$$\hat{Y}_i = \sum_{j=1}^k \text{round}(W_j \cdot 2^q) \cdot \text{round}(X_{i+j-1} \cdot 2^q) + b \quad (5)$$

$\text{round}()$ is the rounding function; q is the quantization scale factor.

In summary, 1D-CNN is very suitable for deployment in devices for UAV structure inspection because the local feature extraction capabilities, and optimized low resource requirements. Further, through quantization technique, the model can also achieve low memory usage and efficient operation.

III. DESIGN AND IMPLEMENTATION

A. Source of experimental data

The different degrees of cutting on the UAV's arms create two types of structural damage: minor cracks in the early stages and major cracks that are completely exposed. Afterwards, data collection will be conducted in an indoor environment. In

addition to considering personnel safety, also avoid interference from external factors.

The sensor this research adopted is GY-521, which has a built-in MPU6050 accelerometer, and is installed near the main body (Inside) and near the motor (Outside), as shown in Fig. 1.

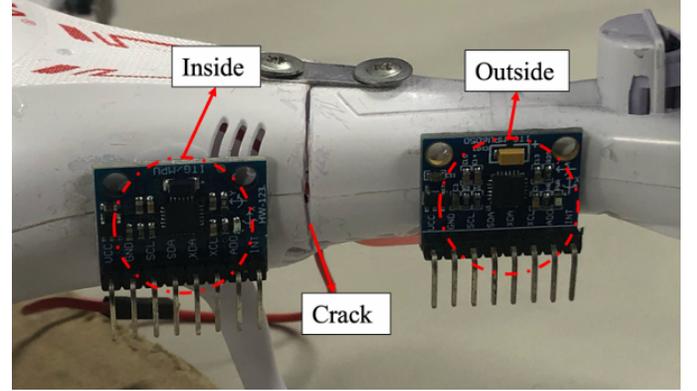


Fig. 1. The locations where the sensors are installed [6].

Totally, 14,506 pieces of data under normal conditions, and 12,648 pieces of data under abnormal conditions were collected, including minor cracks and major cracks.

Then, the data range is scaled to $[-1, 1]$ for standardization to eliminate the impact of unit and magnitude differences on model training. The scaling is calculated as shown in (6).

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}} (Max - Min) + Min \quad (6)$$

Where x' is the scaled value, x is the original sensor data, x_{\max} is the maximum value in the data, and x_{\min} is the minimum value in the data. Max is the maximum value after scaling which is 1, and Min is the minimum value after placing which is -1.

After the data are scaled, using sliding window segmentation, every 120 pieces of data forms a sample with 30 pieces overlaps. Ultimately generating 836 samples, planned as 80% are used for training, 10% are used for verification, and 10% are used for testing.

B. Software and hardware design architecture

This research divides the detected status into three types: normal, minor, and major, and relies on TensorFlow Lite for Microcontrollers (TFLM) for the edge computing deployment capability. For optimizing the memory usage, TFLM converts the 1D-CNN model trained by TensorFlow into TFLite format, and uses quantization technique to compress the weights into 8-bit integers.

In order to ensure the real-time computing capability of the device, The FreeRTOS real-time operating system is also used to implement multi-task management mechanisms for various data reading, processing, and model inference. The hardware framework of this research can be found in Fig. 2.

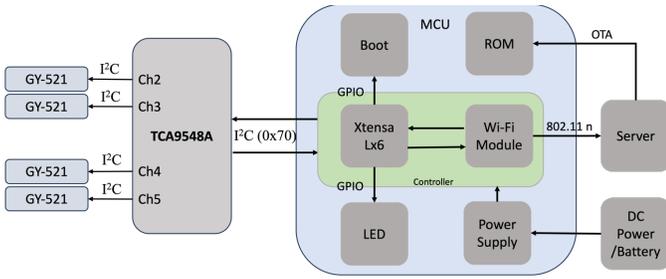


Fig. 2. The system hardware framework of this research [6].

The Adam optimization algorithm is used in the model training phase, and the weights of the model are updated by adaptive learning rate through the moving average index of first-order and second-order moment. The learning rate is set to 0.001, batch Size is 32 for training. The sparse cross entropy (Sparse Cross-Entropy, SCE) as model's loss function. Fig. 3 shows the 1D-CNN model of this research.

TFLM then converts the model into specifications suitable for microcontrollers, which consumes much less memory; the converted model is shown in Fig. 4. Note: TFLM did not yet provide a dedicated 1D convolution kernel during the period of this research. For this reason, Fig. 4 and Fig. 3 are different but equivalent.

For an overview of the operation about FreeRTOS in system, can refer to the flowchart in Fig. 5. The system initialization part mainly creates tasks, initializes hardware (such as GY-521 and I2C interface), allocates semaphores and queues. The data stream processing can be divided into three items:

1. The Data Acquisition Task; is triggered by an interrupt, acquires reading from the sensor and stores in the queue.
2. Inference Task; reads data from the queue and performs model inference to generate classification results.
3. Notification Task; controls the LED or sends an alarm signal based on the inference results.

After the task is executed, the occupied memory is released to provide resources for the later tasks, and avoid affecting subsequent classification judgments. Each task switching and delay will obey pre-set frequency and perform context switching to ensure system stability automatically.

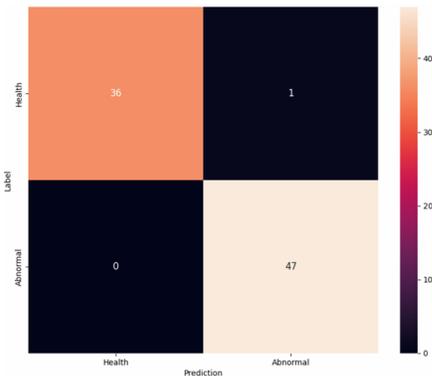


Fig. 6. The performance of quantified model on the test data set [6].

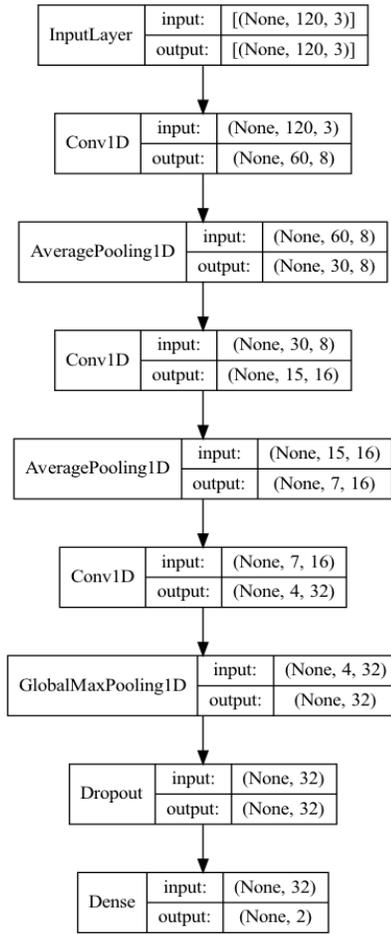


Fig. 3. The 1D-CNN model architecture of this study [6].

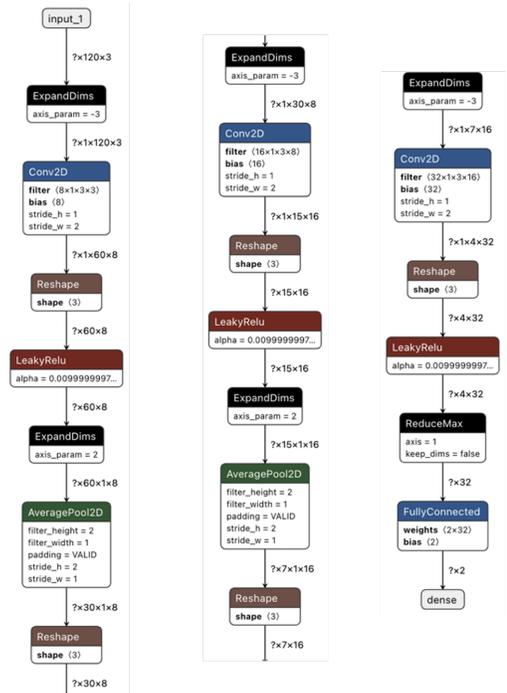


Fig. 4. The architecture of the quantified model in this study after TFLM conversion [6].

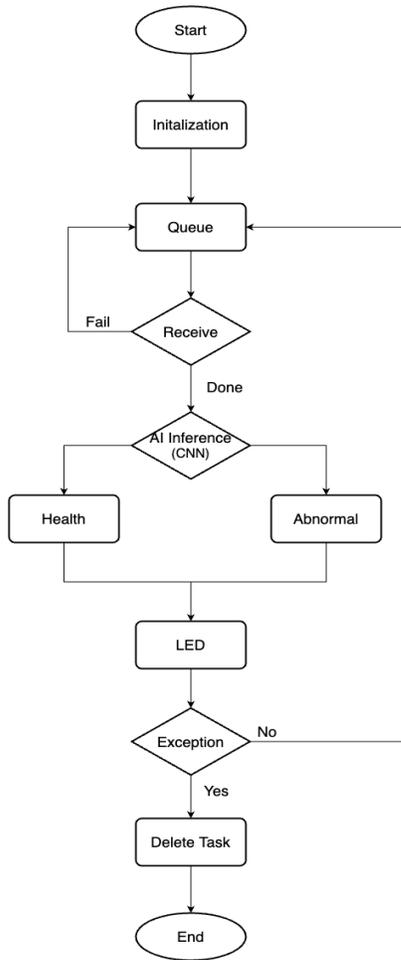


Fig. 5. Software flowchart of this study [6].

IV. VERIFICATION

In terms of verification of the effect, this research adopts a more rigorous inspection method, and both minor and major are classified as structural abnormalities. In this way, it can be verified whether the results can still respond immediately when many unexpected situations such as structural damage caused by bird strikes.

The resulting confusion matrix of quantified model is shown in Fig. 6. The accuracy rate is 0.9881, the precision rate is 0.9792, the recall rate is 1.0, and the F1 score is 0.9895.

The UAV equipped with the results of this research, the weight only increases by 47g and still can fly stably, proving the lightweight and practicality of the hardware design. In the state of minor and major cracks, the LED indicator light can accurately indicate abnormalities, as shown in Fig. 7.



Fig. 7. The actual scenario verified in this study [6].

V. CONCLUSION

This research proposed an edge computing system based on 1D-CNN for UAV arm crack detection, overcomes multiple challenges in UAV structural detection. In order to solve the problem of limited memory and computing power of edge devices, quantization technique is used to compress the 32-bit floating-point model into an 8-bit integer format, which greatly reduces memory usage and computing load. At the same time, facing the problem of insufficient real-time performance of traditional methods, this system directly deploys the deep learning model on edge devices.

By focusing on the selection of acceleration characteristics, this research has greatly reduced the impact of non-structural factors. Finally, the design of this system supports multi-arms detection and classification of cracks, significantly improves the applicability and scalability, provides theoretical and practical basis for the future development of UAV structural inspection.

Compared with the results of [7], the results of this research are more lightweight. As shown in Fig. 8, when this research was verified, the UAV can actually fly without relying on any brackets and other equipment, so it can be seen that the result of this research are more practical. In addition, fuzzy logic requires expert intervention to define the criteria for judgment, while the result of this experiment in this research can automatically extract key features from vibration data, reducing the need for manual labeling.

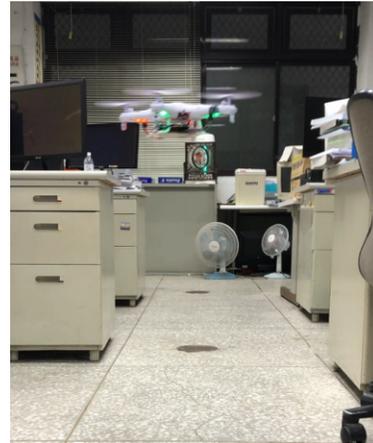


Fig. 8. After carrying the results of this research, the UAV can still take off and hover [6].

VI. FUTURE WORK

This research still has possibility of improvement to the accuracy, stability and applicability. Except upgrading the accelerometers' resolution and speed. Initially, there are still the following topics that can be discussed::

- Use multimodal sensor fusion: Single accelerometer may not capture all structural anomaly signals caused by cracks, such as high-frequency subtle vibrations or structural stress changes. By combining other sensors (such as piezoelectric sensors, strain gauges or acoustic sensors), more dimensions of crack characteristics can

be captured. Specifically, consider adding piezoelectric sensors to monitor high-frequency vibrations or shock waves caused by cracks to supplement the deficiencies of accelerometers in the high-frequency range. Or use integrated strain gauges to measure local strain changes at the crack site to provide direct evidence of structural stress abnormalities. Of course, acoustic sensors can also be combined to analyze the acoustic signals during the crack expansion process to identify the acoustic characteristics of crack generation.

- Dynamically adjust sampling and processing strategies: Currently, fixed frequencies and windows are used for data processing, which may not be adaptable to different sizes of cracks, or signal characteristics in complex environments. Dynamic sampling strategy can be considered, based on the initially detected vibration characteristics, the sampling frequency and data window size are automatically adjusted to adapt to the diversity of crack states. Like adaptive filtering, wavelet transform, or adaptive noise suppression algorithms can dynamically remove the impact of environmental noise on the acceleration signal.
- Enhanced data processing and analysis methods: Existing methods mainly rely on 1D-CNN for time series analysis of vibration signals, probably ignored important information about crack characteristics in the frequency domain. Considering frequency domain analysis, performing Fast Fourier transform (FFT) on the acceleration signal to extract frequency features as auxiliary information, then combining time-frequency domain features for classification. Also, using hybrid models, such as combining 1D-CNN and LSTM (long short-term memory network) to simultaneously capture

the time dependence and frequency characteristics of vibration data.

- Optimization of machine learning models: Existing models only statically classify crack states and may ignore the time evolution characteristics of crack development. Considering train a time series model (such as Transformer) to predict the evolution of the crack state and achieve early warning. Alternatively, other structural health monitoring data might be useful to pre-train model by transfer learning technology. Improving the generalization ability for rare crack patterns.

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