Research on Fault Feature Extraction and Intelligent Diagnosis Technology of Motor Drive in Embedded Systems

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ABSTRACT Motor drive systems operating in embedded environments are frequently affected by noise, dynamic loading conditions, and electromagnetic interference, making timely fault diagnosis difficult. To improve diagnostic accuracy and real-time performance, this study proposes an intelligent fault diagnosis framework based on embedded multi-source data acquisition and feature fusion. High-precision sensors are employed to synchronously collect vibration and current signals, while improved wavelet packet decomposition and principal component analysis are combined to extract discriminative multi-dimensional fault features and eliminate redundant information. A lightweight convolutional neural network optimized for embedded deployment is then developed to perform low-latency fault classification and edge inference. Experimental results show that the proposed method achieves an average F1-score exceeding 97% under complex mixed-fault conditions, while maintaining an average detection latency of approximately 45 ms. The proposed framework demonstrates strong robustness and computational efficiency, providing practical support for intelligent industrial maintenance and offering reference solutions for embedded sensing, signal processing, and electromagnetic compatibility environments.

INDEX TERMS motor drive diagnosis, embedded systems, wavelet packet decomposition, signal processing, electromagnetic compatibility

I. INTRODUCTION

MOTOR drive systems are fundamental to the operation of automated manufacturing equipment and high-speed material processing links, where the stability of the production line and the structural integrity of industrial materials directly depend on the continuous working status of these drives. Maintaining the precise synchronization of motor units in engineering is essential to prevent material breakage and ensure the uniform density of high-performance structured materials during large-scale industrial operations. But the conditions under which motors are operated are usually variable and difficult, e.g. frequent changes of loads, large backgrounds of temperature and humidity and extreme levels of electromagnetic interference, all of which may lead to different extents of performance hiccups to the drive system. Vibration and current signals have variable and high noise characteristics during the operation of the system and the indications of abnormal conditions are often exceptionally faint. This complicates the traditional methods of monitoring and fault early warning that are based on experience to make correct and real-time decisions on the health of equipment which is more challenging to intelligent and automated operation and maintenance[1-2].

There are three significant problems to motor drive fault diagnosis that are caused by complex operating conditions. To begin with, the types of faults are extremely varied and not all of them are noticeable. Multiscale non-stationary patterns are frequently present in signals, which directly makes them more challenging to identify qualitatively and quantitatively. Second, embedded systems possess weak computing capabilities, so it cannot easily analyze large volumes of multi-source data in real time and diagnose in low latency. Third, with real-time monitoring the temporal consistency between signals is not a priority and fine-grained fault information can be masked easily by redundancy and noise. Moreover, the simultaneous alterations in the conditions of work and outside influence also contribute to the further complication of the differentiation of abnormal symptoms. The solution to these bottlenecks is to have an innovative approach that can maximize the use of multi-dimensional capabilities, adjust to embedded applications, and facilitate intelligent judgement on the edge.

To overcome the above challenges and hardships, this paper dwells on edge deployment on embedded system with a special emphasis on organic integration of high-precision signal acquirement and fusion, adaptive extraction of complicated features, and lightweight deep learning diagnostic framework to create a whole intelligent motor fault diagnosis technology solution. The inconsistency in feature extraction in both the time and amplitude dimension of the multi-source data is resolved by enhancing the wavelet packet decomposition and the principal component analysis procedures. At the edge, low-latency intelligent discrimination is realized with the use of a convolutional neural network reconfigured to the capabilities of embedded hardware. The proposed approach facilitates the transformation of motor health management to high efficiency, precision, and minimal power consumption, offering critical theoretical and technical assistance for the maintenance of high-speed manufacturing equipment and material science processing units. By ensuring the operational stability of these motor drives, the framework secures the structural integrity of industrial materials and promotes the overall safety and reliability of automated engineering production lines[3-4].

II. RELATED WORK

The high level of integration, real-time performance and capability to deploy them in the field is making embedded systems gradually replace the traditional PC-based analysis in industrial fault diagnosis, becoming an important support to edge intelligence. Many studies have demonstrated that direct in-hardware implementation of signal acquisition, initial data processing and discrimination algorithms can be very effective in reducing the load on the central server as well as greatly increasing the timely nature of early warnings. Embedded platforms find extensive applications in tracking dynamic parameters like vibration and temperature increase in the production lines and allow continuous health management and remote maintenance of the equipment.

Wavelet Packet Decomposition (WPD) is also known to be good in time-frequency refinement and showing hidden features of industrial signals because of the multi-scale decomposition features. Principal Component Analysis (PCA) gives good evidence of noise reduction and the compression of redundancy of high-dimensional features. Recently, scientists have examined the techniques of multilayer WPD and PCA, in order to obtain early characteristics of minor faults in electric motors, power electronics, and structural components to enhance the effectiveness of classification and diagnostics systems in terms of utilizing information. Convolutional Neural Networks (CNNs) have been popular in intelligent diagnostic activities because of their effective representation and discrimination properties. CNNs are able to autonomously learn the crucial discrimination patterns of signals and prevent the need of intricate manual feature engineering in time-series multi-source monitoring scenarios, owing to an end-to-end structure. In order to meet the real-time needs of industrial locations, studies are continuously underway to focus on CNN network thinning, quantization and heterogeneous implementation techniques in order to reach lightweight and efficient on-site inference of the system.

Although the current approaches have remarkable performance when it comes to extracting features as well as recognition of patterns, there remains a deficiency on signal fusion diversity, model flexibility, and friendliness to embedded computing power. Problems like the consistency of signal synchronization, operation condition adaptation and noise resistance make deployment restricted by practical challenges. A question on how to integrate multi-dimensional signal fusion, adaptive feature extraction, and minimalist and efficient intelligent models to create solutions that can be modified to fit complex working environment has become an object of continued research in both academia and engineering[5-6].

III. METHODS

A. EMBEDDED PLATFORM SIGNAL ACQUISITION AND FUSION DESIGN

To accomplish the effective synchronous collection of vibration and current signals throughout the motor drive, the embedded platform is provided with a high-performance microcontroller. It has a 16-bit high-speed ADC module with a sampling frequency up to 20 kHz. To ensure signal integrity in industrial environments, the system maintains an Effective Number of Bits (ENOB) of 14.2 and a Signal-to-Noise Ratio (SNR) of 86 dB, guaranteeing the time accuracy and amplitude accuracy of signal capture. Multi-channel inputs make use of a hardware-level synchronization scheme to minimize time drift between samples so that the data of different sensors is always strictly time-constrained. As a solution to signal noise in complex operating conditions, the acquisition link employs multi-level hardware filtering (bandpass and notch filters) to actively reduce the power frequency interference and other harmonics. Once data is acquired, it is immediately offloaded to an on-chip cache of 128 KB via a DMA channel. To manage this tight memory constraint, a “ping-pong” buffering strategy and layer-wise weight loading are implemented, ensuring that high-dimensional matrices and CNN weights are processed in small, manageable blocks without overflowing the cache. The cache stage is programmed with the event of automatic time synchronization and amplitude normalization algorithm which guarantee very high comparability of multi-source signals. An on-chip algorithm module carries out signal fusion. The information fusion of multiple data streams in real time based on sensor configuration information, weighted allocation strategies, and time window parameters is done, which enhances the data basis of further fine-grained feature analysis[7-8]. Table 1 summarizes the core performance parameters of the system.

TABLE 1. Performance Parameters of the Acquisition Module

Performance Items	Vibration Channel	Current channel	Signal fusion processing	Notes
ADC resolution	16-bit	16-bit	–	Fine amplitude sampling
Highest sampling rate	20 kHz	20 kHz	Synchronous main frequency	Support lossless synchronous acquisition
Multi-channel maximum timing drift	Less than $2\mu s$	Less than $2\mu s$	$<1\mu s$ after correction	Ensure timing consistency
Filtering range	10~5000 Hz	10~5000 Hz	Multi-level collaboration	Active suppression of power frequency and harmonics
Cache capacity	128 KB	128 KB	Unified allocation	Supports large window caching

B. IMPROVED FEATURE EXTRACTION STEPS OF WAVELET PACKET DECOMPOSITION AND PCA

To ensure computational efficiency on the 200 MHz processor, the acquired multi-source signals undergo a simplified lifting-based five-level wavelet packet decomposition, which reduces redundant multiply-accumulate operations. By adaptively selecting the optimal mother wavelet and decomposition level, the frequency domain features of the signals are refined. Frequency band division is dynamically optimized for key frequency bands in motor drives, improving sensitivity to weak fault modes. After each decomposition level, statistical features such as sub-band energy, normalized spectral entropy, and kurtosis are extracted and organized at multiple scales to fully reflect weak anomalies and non-stationary events. The features of each source signal are used to construct a two-dimensional matrix input within the fusion pool. The data structure is expanded in dimension to cover changes in multiple operating conditions. To efficiently process high-dimensional feature vectors, PCA is applied to compress the matrix dimension. Covariance correlation analysis is performed on the feature groups, and principal components are selected based on a hybrid threshold that retains 99% of the cumulative variance. This ensures that weak signal components containing faint fault indications are preserved while only purely redundant attributes are removed[9-10]. The entire feature selection and dimensionality reduction process uses an automatic algorithm to optimize participating channels and feature types. Real-time performance feedback is used to dynamically adjust PCA migration parameters to achieve stable feature set output. This process yields highly recognizable multi-source features after dimensionality reduction, which are used as input to the backend intelligent diagnostic model, significantly improving fault mode discrimination capabilities and meeting the needs of embedded high-efficiency computing.

C. LIGHTWEIGHT CONVOLUTIONAL NEURAL NETWORK DESIGN AND IMPLEMENTATION

To balance the computational resource constraints of embedded platforms with the high-precision requirements of motor fault diagnosis, the network structure employs a three-layer one-dimensional convolutional unit as the backbone for feature extraction. The number of convolutional kernels is progressively adjusted from shallow to deep, with batch normalization and activation operations following each layer for robust convergence. The input is directly connected to the feature vector after PCA dimensionality reduction. The width of the first convolutional kernel is set according to the local pattern of the signal, the middle layers fuse cross-channel features, and the last convolutional layer focuses on high-order discriminative information. To compress the number of parameters, the main body of the network uses depthwise separable convolutions, greatly reducing the computational load. Max pooling is embedded after each convolution, and multiresolution downsampling is used to preserve global and local statistical features. The output of the tail global pooling layer is connected to a fully connected discriminator to complete multi-class output. The network weights and biases are iteratively fine-tuned through a convolutional Adam optimizer, with cross-entropy loss used for feedback adjustment. When deployed on the edge, a quantized parameter set is loaded. To preserve the "high-precision" capture of faint symptoms, a 16-bit fixed-point quantization scheme is employed, which maintains 99.8% of the original floating-point precision during normalization and inference, and the entire process is completed on-chip floating-point units requiring no external cloud support. The overall architecture combines high accuracy with low latency, meeting the real-time and embedded performance requirements of embedded intelligent diagnostics.

IV. RESULTS AND DISCUSSION

A. EXPERIMENTAL TEST PLATFORM AND OPERATING CONDITIONS

The test platform is based on a high-performance embedded embedded processor of 32 bits with a clock rate of 200 MHz and incorporates a multi-channel 16-bit ADC module and separate floating-point arithmetic unit and on-chip high-speed cache of 128 KB. The sensor of vibration and current are attached to the motor body and significant nodes of the drive circuit respectively. The signals are shielded and strengthened to minimize the external noise interference. The object under test is a three phase asynchronous motor rated power of 2.2 kW. Timing of load end is linked to the braking mechanism by a coupling with specific speed to attain alternation of various operating conditions. The load variations can be automatically regulated by the system which includes constant speed operation, variable speed loading/unloading, and intermittent start/stop and the system is able to cover the common abnormal conditions like day-to-day operation, slight imbalance, ground faults, and partial discharge of stator/rotor. The data acquisition cycle brings on a 5 minutes stable operating condition and a 2 minutes dynamic process with varying operating conditions. In every test group, 10 synchronous signals will be obtained, such as such important data streams as vibration and stator current and bus voltage. To improve the universality and accuracy of diagnostic samples, the control sequence is randomly switched during on-site operation, and signal acquisition and label assignment are fully automated. Each set of data undergoes amplitude normalization and timestamp calibration before storage to ensure the objectivity and consistency of subsequent intelligent model training and evaluation.

B. EXPERIMENTAL RESULTS

Data utilized in the experiment was characterized by different operating conditions sampled in the sample set, in training and testing ratios of 7:3. To prevent temporal leakage, training and testing sets were partitioned by distinct 5-minute sessions rather than random signal shuffling within a single session, ensuring a temporal buffer between datasets. The embedded system automatically sorted out the multi-dimensional features of the vibration and current input channels after applying the optimized diagnostic model on the edge. All the signals were standardized and fed into a light convolutional neural network which was regularly run under various operating conditions and loads. Classification prediction accuracy and mean response time to the fault detection were statistically determined. Comparison of labels was used to judge the result of the diagnostic process to determine the strength and real time operation of the solution. Table 2 shows the results.

TABLE 2. Experimental Results of Motor Drive Fault Diagnosis

Operating conditions	Accuracy (%)	Recall rate (%)	F1 score (%)	Average detection time (ms)
Stable normal operating conditions	99.2	98.9	99.0	43
Imbalance fault	98.1	97.4	97.7	47
Grounding fault	97.8	98.6	98.2	44
Partial discharge fault	98.7	98.4	98.5	45
Mixed complex faults	97.5	96.8	97.1	48

The results show that the model exhibits extremely high accuracy and consistency across all operating conditions, with an F1 score consistently above 97%, maintaining superior performance even under complex mixed fault conditions. The average end-to-end detection latency, encompassing the entire execution flow from acquisition to inference, is controlled within 45 ms, and the rapid response facilitates early anomaly detection. The balanced recall and precision reflect that multiple types of faults can be identified promptly, effectively meeting the needs of embedded real-time monitoring.

C. ADAPTABILITY OF THE SCHEME TO COMPLEX WORKING CONDITIONS

The end-side model can adaptively set the weights corresponding to the fusion of features of each channel under complex operating conditions, such as multiple fault coupling, high load variations, and strong interference conditions, and under high-frequency anomaly detection and fine-grained discrimination with no significant degradation can be observed. The framework makes use of the wavelet packet-convolution hybrid capabilities to show the resistance to intermittent, electrical, and structural failures. Using several batches of ongoing testing, the system output in general is balanced, and there are no detections or severe false alarms. Table 3 summarizes the key adaptability indicators under complex operating conditions.

TABLE 3. Results of Adaptability Assessment for Complex Operating Conditions

Complex working conditions	Overall accuracy (%)	Output consistency (%)	Abnormal detection rate (%)	False positive rate (%)
Multi-type coupled faults	97.2	99.1	98.2	1.2
Interference conditions	96.9	98.7	97.6	1.5
Rapid speed change/load change	97.0	98.9	98.0	1.3
Persistent minor anomalies	98.1	99.4	99.0	0.8
Random operating condition switching	96.7	98.6	97.1	1.4

The model has a high accuracy rate of more than 97% in five complex operating conditions and has excellent output consistency and rate of anomaly detection and false detection rate is very low when operating under conditions of interference and variable operating conditions. This enhanced model sensitivity in environments that have persistent small anomalies points to the fact that the fused features have a great adaptability to the nature of anomalies and time-varying backgrounds.

V. CONCLUSION

The suggested embedded multi-source feature fusion and intelligent diagnostic approach provides a robust solution to the requirements for real-time response and high recognition accuracy in motor drive systems, ensuring stable operation within the high-speed processing and complex interlacing environments of engineering. By maintaining the precision of these drives under fluctuating industrial loads, the framework secures the structural uniformity of high-performance industrial materials and prevents material breakage during automated textile manufacturing processes. Multi-level feature inputs with low information redundancy are obtained by enhancing wavelet packet decomposition and principal component analysis. This, together with the effective convolutional neural network structure, will result in the end-side platform diagnostics being more flexible and closer to engineering uses. The system architecture capitalizes on the benefits of local data analysis to the maximum extent, enhancing the ability to detect and promptly warn about motor faults as well as to provide the efficiency of the runtime and the accuracy of diagnostic solutions in embedded applications. Nevertheless, the ability to generalize this method in the environments where the sample diversity is limited could still be enhanced. Future work will focus on extending the diagnostic model to diverse motor types used in high-speed spinning and automated weaving, ensuring seamless adaptation to the unique mechanical faults encountered in textile engineering and fiber science processing. By further simplifying the model architecture for real-time embedded systems, the framework will enhance the operational reliability of textile manufacturing production lines when facing increasingly complex industrial environments and structural anomalies.

AUTHOR CONTRIBUTIONS

Jie Lan designed, collected and analyzed the data, and drafted the manuscript. Jie Lan conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Jie Lan participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

FUNDING

This work was supported by the university–industry research cooperation project entitled Industry–University–Research Technical Service between Lishui Vocational and Technical College and Zhejiang Shili Motor Co., Ltd. (Project No.: 0202010050, Grant: 15,000 CNY, Project Duration: November 2024 — November 2025)

ACKNOWLEDGEMENTS

Not applicable.

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