



A Dual-State Embedded Vibration Monitoring System for Real-Time Spectral Analysis and Buffered Tri-Axial Data Logging

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Article History

Submitted: To be assigned

Accepted: To be assigned

Published: To be assigned

Abstract

This paper presents a compact embedded vibration-monitoring platform that combines real-time spectral indication with triggered acquisition of raw tri-axial acceleration. The hardware comprises an Arduino Due microcontroller, an MPU6050 microelectromechanical-system accelerometer, a 128×64 organic light-emitting-diode display, and microSD storage. In the online-analysis state, the system samples at 400 samples/s and updates a local spectrum using 64-point Hann-windowed fast Fourier transforms. When the pulse-width-modulated trigger exceeds the prescribed threshold, the firmware enters a recording state in which display refresh and spectral processing are suspended, and the three signed 16-bit acceleration channels are stored in 256-sample binary blocks for 20 s. The resulting record contains 8000 samples, yielding nominal frequency spacings of 6.25 Hz for the online display and 0.05 Hz for full-record post-processing. The available motor test indicates a dominant spectral component at 39.5 Hz and a vibration-velocity root-mean-square value of 3.46 mm/s. The zone-C indication shown in the original MATLAB output is interpreted only within the threshold scheme implemented in the prototype and is not presented as formal ISO 20816-3 compliance because the required machine classification, mounting, measurement-bandwidth, and calibration data were not fully documented. Analytical calculations and controlled numerical evaluations confirm the buffer timing, storage demand, frequency resolution, and behavior of the 10 Hz high-pass operation. The proposed platform is therefore suitable for laboratory instruction, preliminary condition screening, and acquisition of records for subsequent analysis, while calibrated instrumentation and machine-specific validation remain necessary for safety-critical deployment.

Keywords:

Condition monitoring; predictive maintenance; vibration analysis; embedded data logger; fast Fourier transform; MEMS accelerometer; ISO 20816.

1. Introduction

Incipient faults in rotating machinery often develop while the asset remains operational. Progressive bearing degradation, structural looseness, and shaft or coupling misalignment can modify the vibration response before a measurable reduction in functional performance occurs. Vibration monitoring is therefore widely applied in condition-based maintenance and predictive-maintenance programs [1–5]. Spectral components associated with

rotational speed and its harmonics provide direct information on periodic motion, whereas impulsive or modulated responses may indicate bearing, gear, or structural abnormalities. Reliable interpretation nevertheless requires knowledge of operating load, measurement position and direction, sensor mounting, and acquisition-chain performance. Accordingly, an isolated spectral peak should be regarded as an observation requiring engineering assessment rather than as a complete diagnosis.

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Current research increasingly integrates machine-learning methods, edge analytics, and remaining-useful-life estimation into machinery-health monitoring [6–13]. The validity of these methods depends directly on the integrity of the measured data. Sample loss during nonvolatile-memory access, timing jitter, inadequate anti-aliasing, or undocumented preprocessing can distort diagnostic features before classification or prognostic analysis. For embedded monitoring nodes, deterministic acquisition, robust buffering, sensor calibration, and traceable metadata are therefore fundamental design requirements rather than secondary implementation details.

1.1. Related works

Established vibration-diagnostic methods include time-domain statistical indicators, envelope analysis, frequency-domain interpretation, and specialized processing for non-stationary responses [2,4,14–16]. International standards address the complementary requirements of measurement practice and severity evaluation. ISO 13373 specifies general procedures and signal-processing considerations for vibration condition monitoring, whereas ISO 20816 defines evaluation criteria for designated machine groups and support conditions [17–20]. Consequently, a vibration-velocity value in mm/s cannot be interpreted independently of rated power, operating speed, support stiffness, measurement location, direction, and evaluation bandwidth.

Low-cost sensing and embedded computing have extended vibration monitoring to industrial equipment, agricultural machinery, structural systems, and distributed edge nodes [11,21–28]. MEMS-based vibration monitoring has also been demonstrated on unmanned aerial vehicles, including propeller and structural-fault detection [29]. Motor-monitoring studies have combined MEMS accelerometers with embedded inference and TinyML techniques [12,13,30]. Although these platforms reduce hardware cost and facilitate deployment, measurement quality remains governed by sensor bandwidth, noise density, temperature dependence, cross-axis sensitivity, mechanical mounting, and calibration [31–33]. Recent motor-monitoring and edge-computing studies further show that useful vibration features can be extracted on resource-constrained embedded hardware when acquisition and preprocessing are rigorously controlled [11,28,30].

A central architectural issue is the concurrent demand for immediate local visualization and uninterrupted raw-data acquisition. FFT computation, display communication, sensor transactions, and microSD writes

share limited processor time and bus bandwidth, while flash-memory latency may vary substantially between write operations. The proposed architecture addresses this resource conflict by assigning live spectral analysis and buffered recording to mutually exclusive firmware states rather than interleaving both workloads in a single execution loop.

From a communication-systems perspective, the monitoring node may also be regarded as a source of condition data for a wider sensing network. Optical-access research has demonstrated high-capacity transport using intensity-modulation/direct-detection optical orthogonal frequency-division multiplexing in wavelength-division-multiplexed passive optical networks, coherent passive optical networks for 5G transport, and erbium-doped-fiber-amplifier-assisted wavelength-division-multiplexed links [34–36]. Recent studies also investigate peak-to-average power ratio (PAPR) reduction in IM/DD optical OFDM using selective mapping with discrete forest optimization and hybrid whale optimization [37,38]. These works are cited only to contextualize potential communication backbones and do not provide mechanical validation for the present prototype. A future networked implementation could transmit local vibration features or selected raw records through an optical backbone to a remote monitoring platform.

1.2. Novelty and contributions

The principal contribution is not a new fault-classification algorithm, but an embedded acquisition architecture with explicitly defined operating constraints. The main technical contributions are as follows:

1. a two-state firmware structure that isolates real-time FFT visualization from triggered raw-data recording, thereby preventing display and spectral-processing tasks from interfering with storage during the acquisition interval;
2. a documented 400 samples/s sampling schedule, six-byte tri-axial data format, and 256-sample buffering strategy that permit direct verification of timing, memory, and storage requirements;
3. a quantitative comparison between the 64-point on-line spectrum and the 8000-point full-record spectrum, including the corresponding frequency resolutions;
4. a complete signal-processing formulation covering vector magnitude, offset removal, windowing, Fourier transformation, high-pass filtering, numerical integration, detrending, and RMS evaluation;
5. a standards-aware interpretation of the measured motor result that separates the implemented screen-

- ing threshold from formal ISO 20816-3 compliance; and
6. deterministic numerical evaluations of buffer occupancy, data volume, spectral resolution, and high-pass behavior, with all nonexperimental results explicitly identified.

1.3. Paper organization

Section 2 presents the hardware architecture, firmware states, and binary data format. Section 3 formulates the signal-processing chain and defines the associated variables and units. Section 4 reports the embedded operation, the available motor measurement, and the analytical and numerical evaluations. Section 5 provides an architectural comparison with related low-cost systems and identifies the principal limitations. Section 6 summarizes the validated findings and the requirements for further development.

2. System architecture and embedded implementation

2.1. Hardware architecture

The hardware platform is centered on an Arduino Due incorporating a 32-bit ARM Cortex-M3 processor operating at 84 MHz [39]. Vibration is measured using the tri-axial accelerometer channels of an MPU6050 inertial measurement unit; the gyroscope channels are not used in the present implementation [40]. The sensor and the 128×64 organic light-emitting-diode (OLED) display share an inter-integrated-circuit (I2C) bus. The microSD interface is connected through the serial peripheral interface (SPI), and an external pulse-width-modulated (PWM) control signal is applied to an interrupt-capable input.

The laboratory assembly shown in Figure 1 includes the microcontroller, sensing module, OLED display, microSD interface, and status light-emitting diodes (LEDs). This open configuration is appropriate for functional verification on the bench. Deployment in an industrial environment would additionally require a shielded enclosure, strain-relieved and electromagnetically compatible interconnections, a mechanically repeatable sensor mounting arrangement, and appropriate environmental qualification.

Figure 2 summarizes the signal and control paths. The principal design decision is to prevent concurrent display updating and microSD writing during the high-integrity acquisition interval. The sensing hardware remains common to both operating modes, while the active processing path is selected by the firmware state.

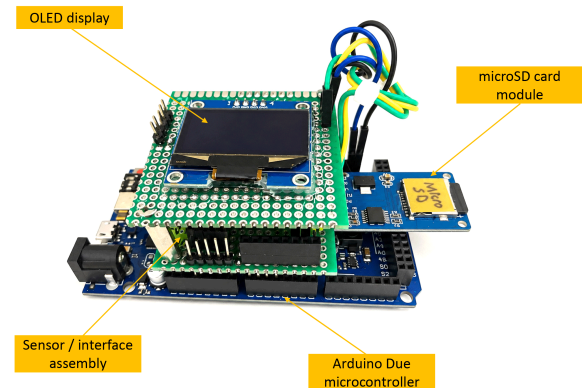


Figure 1: Laboratory prototype of the embedded vibration-monitoring system, showing the Arduino Due, MPU6050 sensor, OLED display, microSD interface, and status indicators. The image was resampled only to improve print readability.

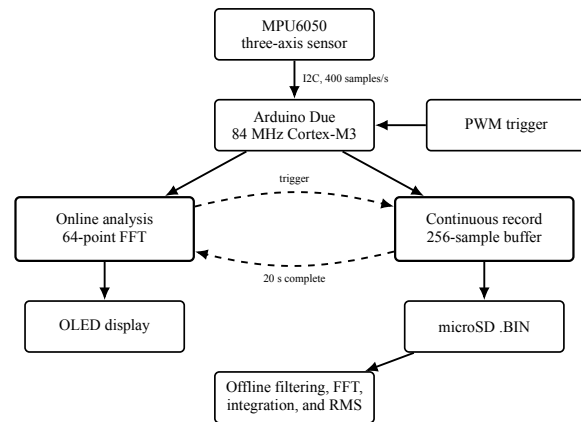


Figure 2: Hardware and data-flow architecture of the proposed platform. Solid arrows denote signal or data transfer, and dashed arrows denote transitions between the online-analysis and recording states.

2.2. Dual-state firmware

The firmware is implemented as a finite-state machine with explicit online-analysis and recording states. Following power-up, the sensor remains stationary for approximately 3 s while the initial offset is estimated, after which the system enters online analysis. The external PWM command is monitored by an interrupt service routine that performs only the minimum operations required to register a state-change request. The transition itself is executed by the main program at a controlled boundary, thereby limiting interrupt-induced sampling jitter.

As illustrated in Figure 3, the online-analysis state acquires 64 acceleration-magnitude samples, removes the frame mean, applies the Hann window, and computes the FFT. In the recording state, FFT processing and routine display updates are disabled. The three raw signed 16-bit

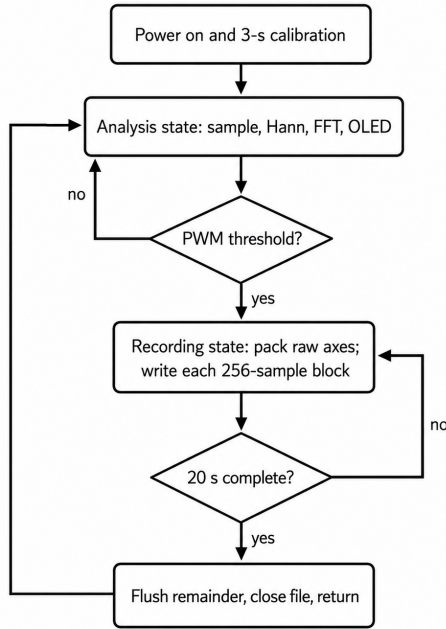


Figure 3: Finite-state-machine sequence implemented in the embedded firmware. FFT computation and routine display updates are suspended during recording, and binary block transfers are performed exclusively in the recording state.

acceleration channels are packed into six bytes per sample, and each complete 256-sample buffer is transferred to the microSD card as a 1536 byte block. After 20 s, the residual samples are written, the data file is closed, and control returns to the online-analysis state.

2.2.1. Online-analysis state

The online-analysis state operates at a sampling frequency of 400 Hz, corresponding to a Nyquist frequency of 200 Hz. Each 64-sample frame spans 0.16 s. A Hann window is applied before FFT computation to reduce spectral leakage when signal components are not coherent with the frame duration. The transform is evaluated using the `arduinoFFT` library, and the resulting magnitudes are rendered on the OLED using the `U8g2` graphics library [41,42]. The resulting bin spacing of 6.25 Hz is adequate for identifying a dominant frequency region but is insufficient for resolving closely spaced components.

Accordingly, the display in Figure 4 is intended as an immediate condition-screening interface rather than as a precision spectrum analyzer. It enables verification of sensor operation, the presence of vibration, and changes in the dominant spectral band during field inspection.

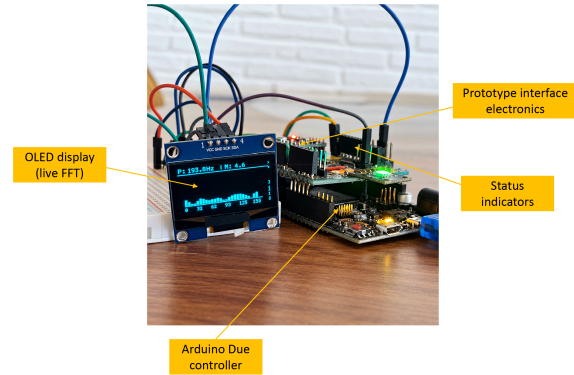


Figure 4: OLED display during the online-analysis state. The 64-point FFT provides rapid indication of the dominant spectral region but not high-resolution frequency discrimination.

2.2.2. Continuous-recording state

Recording is initiated when the measured PWM pulse width reaches the configured threshold; the prototype implementation used a value of approximately 1600 μ s. At the next controlled transition point, the OLED is held on a fixed recording indication and the FFT routine is disabled. Suspending these variable-duration tasks for the 20 s interval reduces contention for processor time and communication resources during data acquisition.

Each sampling instant produces three signed 16-bit acceleration values, corresponding to six bytes per tri-axial sample. The 256-sample buffer therefore stores 1536 byte and reaches capacity every 0.64 s. A complete 20 s acquisition comprises 31 full block transfers followed by a final 64-sample transfer. Binary storage is adopted to minimize conversion overhead and storage demand relative to formatted decimal text.

3. Signal-processing and mathematical formulation

This section formulates the complete signal-processing sequence used for online and offline analysis. Each operation is defined mathematically, and Table 1 summarizes the corresponding symbols and physical units.

3.1. Tri-axial magnitude, offset removal, and SI conversion

Let $a_x[n]$, $a_y[n]$, and $a_z[n]$ denote the calibrated accelerometer channels at sample index n . When the channels are expressed in units of gravitational acceleration, the scalar vector magnitude is

$$M[n] = \sqrt{a_x^2[n] + a_y^2[n] + a_z^2[n]}. \quad (1)$$

The Euclidean magnitude in Eq. (1) reduces dependence on sensor orientation; however, it also suppresses directional information that may be important for fault localization [31]. It should therefore be used as a complementary indicator rather than as a substitute for axis-specific analysis.

The mean magnitude over N samples is

$$\mu_M = \frac{1}{N} \sum_{n=0}^{N-1} M[n], \quad (2)$$

and the dynamic acceleration used for subsequent processing is

$$a_d[n] = g_0(M[n] - \mu_M), \quad (3)$$

where $g_0 = 9.80665 \text{ m/s}^2$ denotes standard gravitational acceleration. The mean-removal operation eliminates the constant component but does not suppress low-frequency drift or motion below the subsequent high-pass cutoff [18, 43].

3.2. Windowed FFT and frequency grid

For a frame $x[n]$ of N dynamic-acceleration samples, the discrete Fourier transform is

$$X[k] = \sum_{n=0}^{N-1} x[n] e^{-j2\pi kn/N}, \quad k = 0, \dots, N-1, \quad (4)$$

where $j = \sqrt{-1}$. The embedded implementation evaluates Eq. (4) with a radix-2 FFT, reducing the computational order from $\mathcal{O}(N^2)$ to $\mathcal{O}(N \log_2 N)$ [43,44].

Before transformation, the frame is multiplied by the Hann window

$$w[n] = \frac{1}{2} \left[1 - \cos\left(\frac{2\pi n}{N-1}\right) \right]. \quad (5)$$

The Hann window reduces endpoint discontinuities and spectral leakage, while increasing main-lobe width and modifying the amplitude scale [45,46]. The physical frequency associated with bin k is

$$f_k = \frac{kF_s}{N}, \quad (6)$$

where F_s is the sampling frequency [43].

3.3. Frequency-domain high-pass filtering and inverse transform

Direct integration of measured acceleration can produce substantial low-frequency drift in the estimated velocity because the integration gain increases as frequency approaches zero. The offline processing therefore applies

the following symmetric frequency-domain high-pass mask:

$$Y[k] = \begin{cases} 0, & |f_k| < f_c, \\ X[k], & |f_k| \geq f_c, \end{cases} \quad (7)$$

where the adopted cutoff is $f_c = 10 \text{ Hz}$. The filtered time signal is reconstructed by

$$y[n] = \frac{1}{N} \sum_{k=0}^{N-1} Y[k] e^{j2\pi kn/N}. \quad (8)$$

Equations (7) and (8) implement a deterministic frequency-domain filter [43,47]. Although the rectangular mask is computationally simple, its abrupt transition produces an oscillatory impulse response. A deployment-oriented implementation should compare this approach with a designed finite-impulse-response or infinite-impulse-response high-pass filter and should define the passband in accordance with the applicable evaluation standard.

3.4. Acceleration-to-velocity conversion, detrending, and RMS

In the frequency domain, acceleration and velocity are related by

$$V(f) = \frac{A(f)}{j2\pi f}, \quad f \neq 0, \quad (9)$$

which demonstrates the strong amplification of residual low-frequency components during acceleration-to-velocity conversion [18,43]. In the implemented processing chain, the filtered acceleration is integrated in the time domain using the trapezoidal rule:

$$v_r[n] = v_r[n-1] + \frac{T_s}{2} (y[n] + y[n-1]), \quad (10)$$

where $T_s = 1/F_s$ is the sampling interval. This update is a standard second-order numerical-integration approximation [43,47]. A least-squares linear trend is subsequently removed,

$$v[n] = 10^3(v_r[n] - p_0 - p_1 t_n), \quad (11)$$

where $t_n = nT_s$ and the factor 10^3 converts m/s to mm/s. The baseline-removal form in Eq. (11) is standard detrending practice [43,47]. Finally, the velocity root-mean-square (RMS) value over the selected record is

$$v_{\text{RMS}} = \sqrt{\frac{1}{N} \sum_{n=0}^{N-1} v^2[n]}. \quad (12)$$

The RMS quantity in Eq. (12) is consistent with the general vibration-velocity metric employed in ISO 20816.

Formal evaluation, however, requires the correct machine group, support condition, measurement position and direction, and frequency range [19,20].

3.5. Resolution and storage equations

The nominal frequency spacing of an N -sample transform follows the standard DFT frequency grid [43]:

$$\Delta f = \frac{F_s}{N}. \quad (13)$$

At $F_s = 400$ Hz, Eq. (13) gives 6.25 Hz for $N = 64$ and 0.05 Hz for $N = 8000$. The binary throughput and total record size are

$$R_B = F_s N_a N_b, \quad D = T R_B, \quad (14)$$

where $N_a = 3$ axes, $N_b = 2$ bytes per axis, and $T = 20$ s. Using the sensor word length and the implemented storage format [39,40], Eq. (14) gives $R_B = 2400$ byte/s and $D = 48\,000$ byte, equivalent to 46.875 KiB for 1 KiB=1024 bytes.

4. Results and discussion

4.1. Embedded operation and storage integrity

The prototype exhibited the intended state-dependent operation: live analysis was indicated during normal monitoring, and a dedicated recording indication was activated during microSD acquisition. The reported 20 s measurement at 400 samples/s was completed without an observed loss of samples. Because the available implementation did not provide a monotonic sample counter, per-sample timestamps, a logic-analyzer record, or an automatically reported file-length check, the present evidence supports dimensional consistency with an 8000-sample acquisition but does not constitute a formal sample-integrity test.

Figure 5 provides a deterministic evaluation of buffer occupancy based on the implemented sampling and block sizes. The buffer reaches capacity every 0.64 s, so data are transferred in comparatively large blocks rather than through 400 individual write transactions per second. This arrangement reduces file-system overhead, although worst-case memory-card latency must still be verified experimentally.

The storage analysis in Figure 5 also evaluates alternative sampling rates using Eq. (14). At 400 samples/s, each 20 s record requires 46.875 KiB. Increasing the rate to 1600 samples/s would increase both the data throughput and storage demand by a factor of four and would raise the Nyquist frequency to 800 Hz. Such an extension

could improve sensitivity to higher-frequency bearing responses, but it would require renewed verification of the sensor noise floor, I2C transaction timing, anti-aliasing performance, and worst-case microSD write latency.

4.2. Reported motor record

Figure 6 presents the available motor measurement. The upper panel shows the filtered acceleration-magnitude waveform, and the lower panel shows the corresponding one-sided spectrum. The analysis identifies a dominant component at 39.5 Hz and a vibration-velocity RMS of 3.46 mm/s. This component may correspond to rotational motion, a harmonic, an electrical excitation, or a structural response; however, the absence of an independent shaft-speed reference prevents a defensible assignment of mechanical order.

The zone-C indication in the MATLAB output was obtained from thresholds of 1.12, 2.80, and 7.10 mm/s. ISO 20816-3:2022 instead applies machine-group- and support-specific criteria to industrial machinery above 15 kW within a defined operating-speed range [20]. Because the rated power, operating speed, support condition, measurement location and direction, and complete evaluation bandwidth were not documented, the displayed zone is interpreted as an implementation-specific screening result rather than as a standards-compliant machine classification.

4.3. Frequency-resolution validation

Figure 7 quantifies the effect of transform length using a controlled numerical signal containing components at 39.5 Hz and 42.0 Hz. With a bin spacing of 6.25 Hz, the 64-point online transform represents the two components as a single broad spectral region. The 8000-point full-record transform, for which the nominal spacing is 0.05 Hz, resolves the two frequencies separately. This evaluation verifies the resolution predicted by Eq. (13) and does not imply the presence of a second component in the measured motor data.

The finer bin spacing of the full-record transform does not guarantee superior diagnostic performance under all operating conditions. The calculation assumes that the 20 s interval is sufficiently stationary. Variations in speed or load broaden spectral components and may obscure the corresponding mechanical orders. For nonstationary operation, overlapping short-time spectra or speed-referenced order tracking are more appropriate than a single transform of the complete record [14,18].

Table 1: Mathematical symbols and units. “Dimensionless” includes indices, counts, normalized window coefficients, and unscaled FFT factors.

Symbol	Meaning	Unit
n, k	Time-sample and frequency-bin indices	dimensionless
N	Number of samples in the processed frame or record	samples (count)
$a_x[n], a_y[n], a_z[n]$	Calibrated axis accelerations before SI conversion	g
$M[n], \mu_M$	Tri-axial magnitude and its sample mean	g
g_0	Standard gravitational acceleration	m/s^2
$a_d[n], x[n], y[n]$	Dynamic, input, and filtered acceleration	m/s^2
$w[n]$	Hann-window coefficient	dimensionless
$X[k], Y[k]$	Unnormalized DFT coefficients before and after masking; units follow the acceleration convention	m/s^2 under the stated unnormalized convention
j	Imaginary unit	dimensionless
F_s	Sampling frequency	Hz
T_s	Sampling interval, $1/F_s$	s
$f_k, f, f_c, \Delta f$	Bin frequency, continuous frequency variable, high-pass cutoff, and frequency spacing	Hz
$A(f), V(f)$	Acceleration and velocity spectra	m/s^2 and m/s
$v_r[n]$	Integrated velocity before detrending	m/s
$v[n], v_{RMS}$	Detrended vibration velocity and its RMS value	mm/s
p_0	Fitted constant velocity offset	m/s
p_1	Fitted linear velocity-drift coefficient	m/s^2
t_n, T	Sample time and total recording time	s
N_a, N_b	Number of axes and number of bytes per axis	dimensionless count and byte/axis
R_B, D	Binary data rate and total record size	byte/s and byte

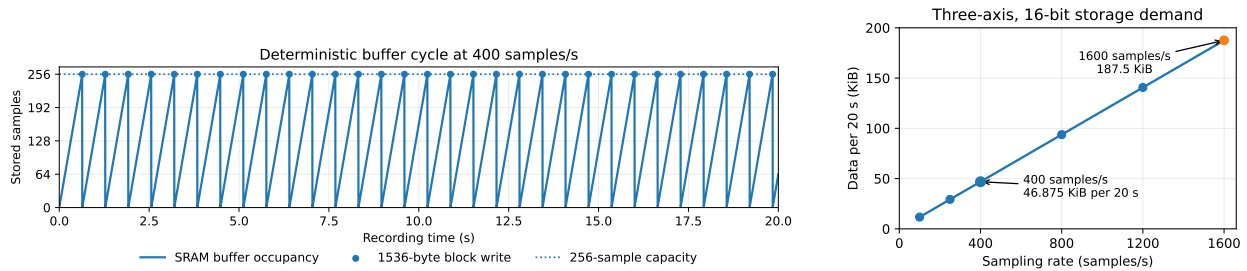


Figure 5: Calculated acquisition characteristics. Left: buffer occupancy during a 20 s record; the dotted line marks the 256-sample capacity and the markers indicate the 31 complete 1536 byte block transfers. Right: storage demand for a 20 s, three-axis, 16-bit record as a function of sampling frequency, including the 1600 samples/s case.

4.4. High-pass-filter validation

Before numerical integration, the implemented processing chain suppresses spectral components below 10 Hz. Figure 8 applies this operation to a controlled numerical signal containing low-frequency drift, components at 39.5 Hz and a higher frequency, and broadband noise. The time- and frequency-domain results confirm suppression of the slowly varying component while preserving the components above the cutoff.

The evaluation also demonstrates the limitation of an abrupt rectangular mask. The response changes from complete rejection to complete transmission at a single frequency bin, so the estimated amplitude of a component

near 10 Hz is highly sensitive to its exact frequency. A revised implementation should select the cutoff according to machine speed and the applicable standard and should compare the current mask with a specified FIR or IIR filter having documented transition-band, magnitude, and phase characteristics.

ISO 20816 Assessment | Velocity RMS: 3.46 mm/s | Status: ZONE C (Warning / Planned Maintenance Required)

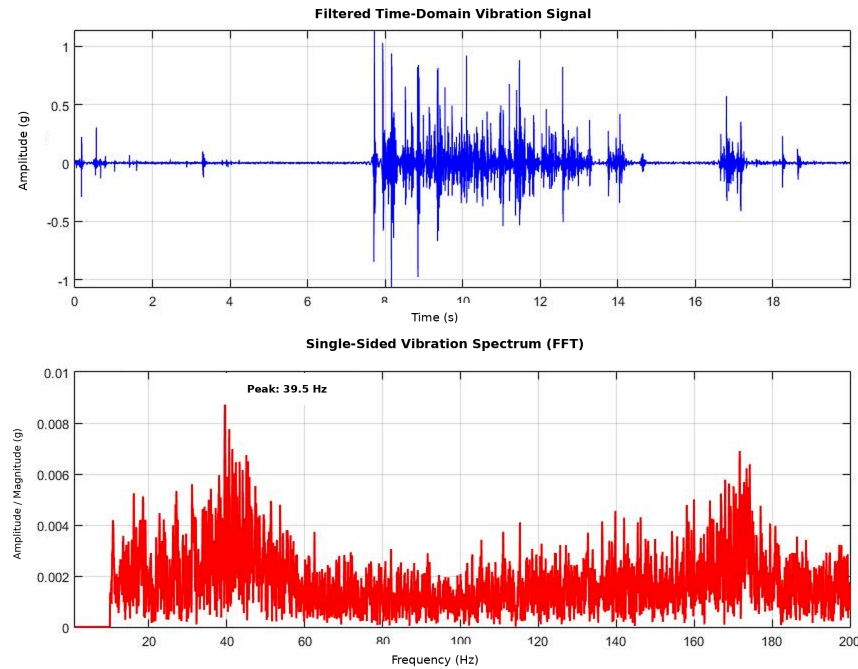


Figure 6: MATLAB analysis of the motor measurement. The record indicates a dominant component at 39.5 Hz and a vibration-velocity RMS of 3.46 mm/s. The displayed zone is interpreted as a screening result because the machine category and complete ISO evaluation conditions were not documented.

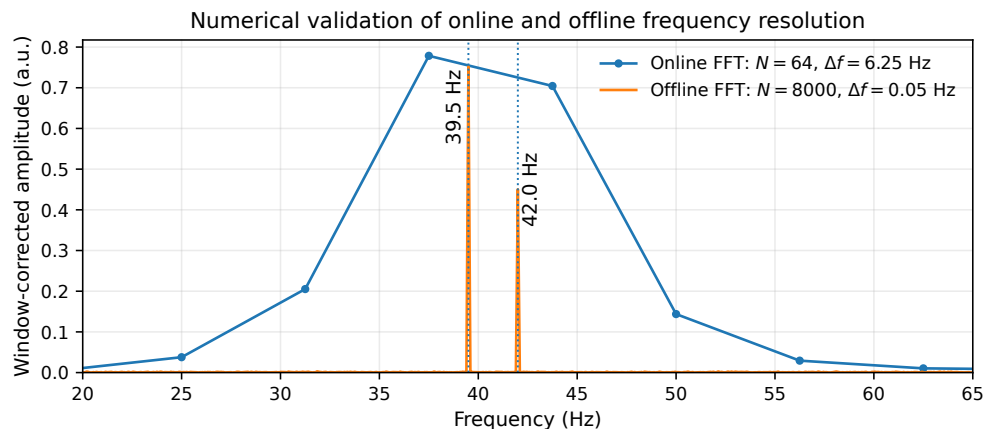


Figure 7: Numerical comparison of the 64-point online transform and the 8000-point full-record transform for two closely spaced tones. The plot demonstrates the frequency-resolution difference between the two operating modes and does not represent an additional measured motor component.

5. Comparison with previous work and limitations

5.1. Comparison with related low-cost systems

Table 2 provides an architectural comparison rather than a direct ranking of measurement accuracy because the

cited systems employ different sensors, target machines, bandwidths, and validation protocols. Within this scope, the principal distinction of the present platform is the integration of online spectral indication and state-isolated buffered recording on a single microcontroller.

Table 2: Architectural comparison with representative low-cost vibration and acceleration data-acquisition systems. NR means not reported in the cited publication at the level needed for this comparison.

Study	Main hardware	Acquisition emphasis	Local analysis/display	Storage/communication	Comparative assessment
Villarroel et al. [21]	STM32F407, external ADC and accelerometer	Industrial vibration measurement	Embedded conditioning and processing	Wireless module	Dedicated analog front end and wireless transfer; higher hardware complexity.
Mystkowski et al. [22]	Low-cost accelerometer nodes for a rotary tedder	Agricultural machine monitoring	Application-specific monitoring	Multi-node prototype	Distributed field deployment; no state-separated local FFT and recording.
Jakobsen [23]	ADXL1002, ultrasonic MEMS microphone, radio-enabled node	Wide-band vibration and acoustic sensing	Edge-ready sensor platform	LoRa and Bluetooth Low Energy	Wide sensing bandwidth and dual wireless links; higher integration and power demand.
Özdemir and Kömeç Mutlu [24]	Raspberry Pi, ADXL355 or geophone	Structural and ground-motion recording	Web-supported analysis	microSD and network functions	Calibrated structural monitoring with network analysis; larger, higher-power single-board-computer platform.
Ivanov [25]	Configurable low-cost accelerometer logger	File-based acceleration collection	Configuration through SD-card data	SD card	Configurable file-based acquisition; no real-time spectral display.
Sönmezocak [29]	MEMS vibration acquisition for UAVs	Propeller and structural fault discrimination	Intelligent feature/classification workflow	Research platform	UAV fault classification; different application target and processing workflow.
Present work	Arduino Due, MPU6050, OLED, microSD	400 Hz tri-axial motor vibration	64-point live FFT and bar display	256-sample binary buffering	Single-microcontroller live FFT and triggered logging; constrained by sensor bandwidth, calibration status, and machine metadata.

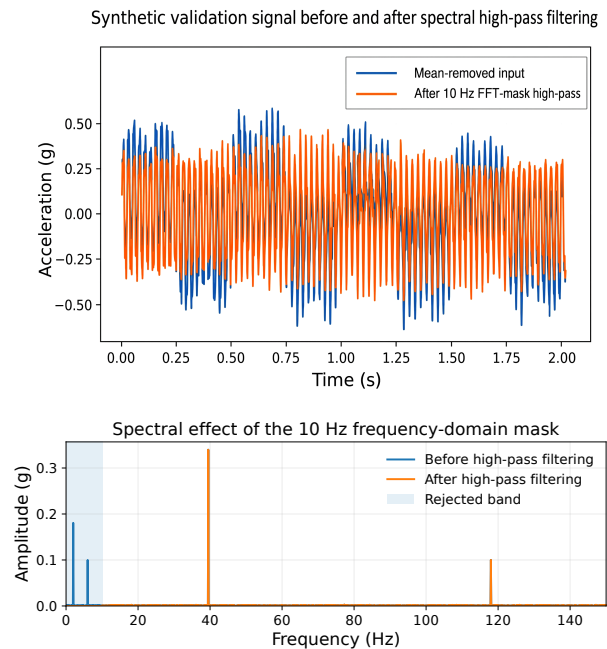


Figure 8: Numerical evaluation of the 10 Hz frequency-domain high-pass operation. Top: time-domain response before and after filtering. Bottom: corresponding spectra with the rejected band indicated. The curves are analytical test signals and not measured motor data.

5.2. Limitations and required corrections for deployment

The economic and implementation advantages of the prototype must be considered together with its measurement and deployment limitations.

The MPU6050 is intended primarily for general embedded and inertial-sensing applications rather than for traceably calibrated industrial vibration measurement. Before amplitude estimates are used for acceptance or protection decisions, the sensor scale factor, dynamic frequency response, noise density, temperature sensitivity, cross-axis coupling, and mounting response should be characterized against a reference accelerometer. Static orientation tests can identify offset and large scale-factor errors but cannot establish dynamic amplitude accuracy over the required frequency band [31–33].

A sampling frequency of 400 Hz sets the Nyquist limit at 200 Hz, while the practical measurement band is lower when an anti-aliasing margin is included. This range can capture rotational frequency and several low-order harmonics for many machines, but it excludes a substantial portion of the high-frequency response used for early bearing-impact detection [2,3]. The current configuration is therefore most appropriately classified as a low-frequency screening platform.

The vector magnitude in Eq. (1) reduces orientation dependence but combines the three axes nonlinearly and eliminates directional information. Horizontal, vertical, and axial measurements should therefore be retained and analyzed separately, with the vector magnitude reported only as an additional summary indicator.

The motor experiment did not include an independent shaft-speed measurement. A tachometer or encoder is required for order tracking and for distinguishing shaft-synchronous vibration from electrical excitation and structural resonance. Without speed data, the 39.5 Hz component can be reported accurately as an observed frequency, but its physical origin cannot be established.

Verification of lossless acquisition requires direct timing and data-integrity evidence. Future firmware should store a monotonic sample index or timestamp, expose buffer-overflow conditions, and report the final record length. Logic-analyzer measurements and repeated tests using memory cards with different latency characteristics are also required to quantify worst-case write performance.

Finally, an ISO-oriented RMS assessment requires the machine data that determine the applicable evaluation procedure, including rated power, operating speed, support classification, measurement position and direction, operating load, filter and integration bandwidth, and calibration uncertainty. Until these parameters are documented, the displayed zone should be used only as an inspection indicator and not as the basis for an automatic protection action.

6. Conclusion

A dual-state embedded architecture has been developed to combine immediate spectral indication with a dedicated interval of buffered raw-data acquisition. In the online-analysis state, the platform samples at 400 samples/s and updates a 64-point FFT display. In the triggered recording state, it stores tri-axial 16-bit measurements in 256-sample blocks for 20 s. The resulting 8000-sample record occupies 48 000 byte, the buffer-transfer period is 0.64 s, and the nominal full-record frequency spacing is 0.05 Hz. Independent analytical and numerical evaluations confirm these timing, storage, resolution, and high-pass-filter characteristics.

The available motor analysis indicates a dominant spectral component at 39.5 Hz and a vibration-velocity RMS of 3.46 mm/s. The zone-C indication generated by the original implementation is retained only as an implementation-specific screening output. It does not demonstrate ISO 20816-3 compliance because the required machine classification, support condition, speed,

measurement direction, evaluation bandwidth, and dynamic calibration information were not available.

The present system is appropriate for engineering education, preliminary condition assessment, and acquisition of data for subsequent analysis. Deployment as part of an industrial monitoring or protection system would require traceable dynamic calibration, verified anti-aliasing, axis-specific analysis, independent speed measurement, explicit sample-loss diagnostics, repeatability testing, and machine-specific application of the relevant vibration standard.

Funding

This work was supported by the Scientific Research Projects Coordination Unit of Istanbul Yeni Yuzyil University under Project Code TSA-2026-68 (Project ID: 68).

Acknowledgements

The authors thank the Scientific Research Projects Coordination Unit of Istanbul Yeni Yuzyil University for supporting the project.

Authors' Contributions

Conceptualization: B.S., T.S., and S.K.; Methodology: B.S., M.A., and T.S.; Software: B.S. and A.C.; Validation: M.A., T.S., and S.K.; Formal analysis: M.A. and S.Ö.; Investigation: B.S., S.Ö., and F.T.; Resources: A.C. and F.T.; Data curation: B.S. and S.Ö.; Writing—original draft preparation: B.S. and M.A.; Writing—review and editing: M.A., T.S., and S.K.; Visualization: B.S. and A.C.; Supervision: T.S. and S.K.; Project administration: T.S. and S.K.; Funding acquisition: T.S. and S.K. All authors reviewed and approved the final manuscript.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

AI Disclosure

The AI-based tool Grammarly was used solely for language editing and formatting. No AI tool was used to generate or paraphrase the scientific content of the manuscript. The authors take full responsibility for the accuracy, originality, and integrity of the work.

Figure Originality

Figures 1 and 4 are original and have not been reproduced or adapted from previously published sources.

Availability of Data and Materials

The full dataset generated during the ongoing research project is not currently publicly available due to the active and continuing nature of the project. The specific measurement record presented in this manuscript (Figure 6) is available from the corresponding author upon reasonable request.

Consent for Publication

Not applicable.

List of Abbreviations

ADC	analog-to-digital converter
BLE	Bluetooth Low Energy
DFT	discrete Fourier transform
FFT	fast Fourier transform
FIR	finite-impulse-response
I2C	inter-integrated circuit
IIR	infinite-impulse-response
ISO	International Organization for Standardization
KiB	kibibyte
LED	light-emitting diode
LoRa	Long Range low-power wireless communication
MATLAB	MathWorks numerical computing environment
MEMS	microelectromechanical system
OLED	organic light-emitting diode
PWM	pulse-width modulation
RMS	root mean square
SD	Secure Digital
SPI	serial peripheral interface
SRAM	static random-access memory
TinyML	Tiny Machine Learning
UAV	unmanned aerial vehicle

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