

Labview-Based Adaptive Environmental Noise Monitoring And Source Classification System

Aniritha S¹, Rithanya S¹, Ajissa Jasmin¹ Dr. Saravanakumar R¹

¹school Of Electrical And Electronics Engineering, Vellore Institute Of Technology,Vellore,India

* Corresponding Author : Rsaravanakumar@Vit.Ac.In

*Corresponding Author : Aniritha.S2024@Vitstudent.Ac.In

Abstract. Environmental noise monitoring systems commonly focus on sound-level measurement, while source-aware interpretation and adaptive detection are often treated as separate functions. This work presents a low-cost LabVIEW-based framework for real-time environmental noise monitoring and source classification. An electret microphone and LM358-based signal-conditioning stage acquire the acoustic signal, while an Arduino Nano provides analog-to-digital conversion and serial communication with LabVIEW. The software computes the root-mean-square (RMS) magnitude, calibrated sound level, fast Fourier transform (FFT), equivalent continuous sound level (Leq), maximum sound level (Lmax), and duration of threshold violation. Instead of using only a fixed alarm level, the proposed monitoring strategy estimates the local background-noise condition and adapts the detection threshold to reduce unnecessary alerts. Frequency-domain features are then used to distinguish representative environmental sources such as traffic/engine noise, horns, speech, music, and construction noise. A LabVIEW dashboard provides real-time visualization, alerts and data logging. The hardware prototype has been integrated and the Arduino-LabVIEW interface and experimental validation are being completed. The final evaluation will compare the prototype against a reference sound-level meter and quantify measurement error and classification performance.

Keywords: environmental noise; LabVIEW; Arduino Nano; FFT; adaptive threshold; sound-source classification; Leq

I. INTRODUCTION

Environmental noise is a persistent urban environmental concern arising from transportation, construction, industrial activity and leisure sources. The World Health Organization identifies environmental noise as an important public-health issue and provides evidence-based guidance for reducing harmful exposure [1]. Consequently, continuous monitoring is useful not only for observing sound levels but also for identifying when and why elevated acoustic activity occurs.

Conventional sound-level meters provide accurate level measurements, but continuous deployment of professional instruments can be expensive. Recent research has therefore investigated low-cost acoustic sensing platforms. AudioMoth demonstrated that compact, low-cost hardware can support long-duration acoustic monitoring [2], while other systems have combined low-cost sensing with acoustic detection,

wireless networking and sound classification [3,4]. Environmental sound classification research has also developed increasingly sophisticated feature extraction and machine-learning approaches for heterogeneous acoustic events [5,6].

The present work addresses a practical implementation gap between these directions. The objective is not to replace laboratory-grade sound-level meters or to claim state-of-the-art machine-learning classification. Instead, the work develops an accessible LabVIEW-centered monitoring platform that combines low-cost acoustic acquisition, real-time signal processing, adaptive environmental thresholding, exposure-related metrics and source classification in one system. This integration is intended for educational, laboratory and preliminary field-monitoring applications.

The main contributions are: (i) a low-cost microphone, conditioning and Arduino acquisition chain; (ii) a LabVIEW real-time processing and visualization

framework; (iii) adaptive background-noise thresholding rather than a single fixed detection limit; (iv) computation of RMS, calibrated dB, Leq, Lmax and violation duration; and (v) frequency-domain source classification with visual/audio alerts and logging. The classification stage is deliberately treated as a lightweight, interpretable method whose performance must be experimentally quantified.

II. RELATED WORK

Low-cost acoustic monitoring has been explored using embedded and open-source hardware. Hill et al. introduced AudioMoth as a low-cost, full-spectrum acoustic device for environmental monitoring, demonstrating the feasibility of compact acoustic sensing outside conventional laboratory equipment [2]. Prince et al. investigated deployment of acoustic detection algorithms on low-cost open-source sensors, showing the relevance of onboard signal processing for environmental monitoring [3]. More recent work has combined low-cost sensing with wireless networks and classification for long-term environmental noise monitoring [4].

Environmental sound classification is a broader research area. Bansal and Garg reviewed common datasets, features and classifiers used in environmental sound classification and highlighted the importance of selecting features appropriate to the target sound classes [5]. Mu et al. demonstrated temporal-frequency attention for environmental sound classification, illustrating the complexity of real-world sound events [6]. These studies indicate that simple frequency boundaries may be insufficient when sound classes overlap.

LabVIEW has also been used for acoustic signal processing and adaptive noise-related applications. Kumar and Manjunath reported a LabVIEW implementation of adaptive noise cancellation, where an adaptive filter is used to suppress unwanted noise from a desired signal [7]. The present work uses the term adaptive differently: the system adapts the environmental detection threshold according to the estimated background sound level. It therefore performs adaptive detection, not adaptive noise cancellation.

The literature indicates that low-cost monitoring, acoustic classification and adaptive signal processing are established research directions. The focus of this paper is their integration into a compact LabVIEW-based prototype with an explicit validation procedure. The intended contribution is therefore the system-level combination and practical implementation, not the individual use of FFT, RMS or Arduino.

III. SYSTEM DESIGN AND METHODOLOGY

1. Hardware architecture

The sensing chain consists of an electret microphone, an LM358-based amplification and signal-conditioning stage, an Arduino Nano, and local indication through an LCD/LED/buzzer arrangement. The microphone converts acoustic pressure variations into a low-level electrical signal. The LM358 stage amplifies and conditions the signal so that it can be sampled by the Arduino Nano ADC. The sampled values are transferred to the LabVIEW application through a USB serial link. This architecture was selected to keep the prototype low-cost while retaining access to raw time-domain samples required for signal analysis.

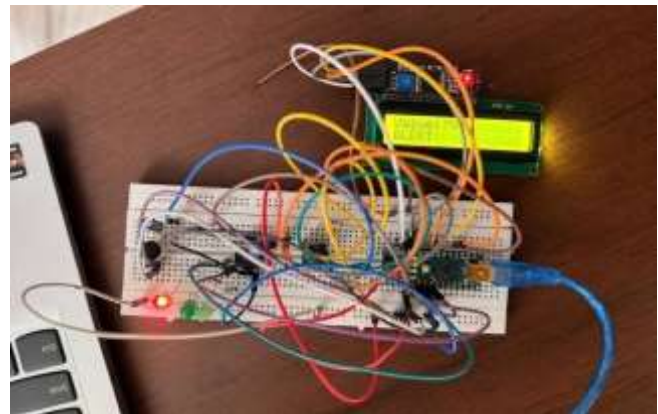


Fig.1. Hardware prototype showing the alert condition, with the red LED activated and the LCD displaying the 'ALERT' status when the detected noise level exceeds the adaptive threshold.

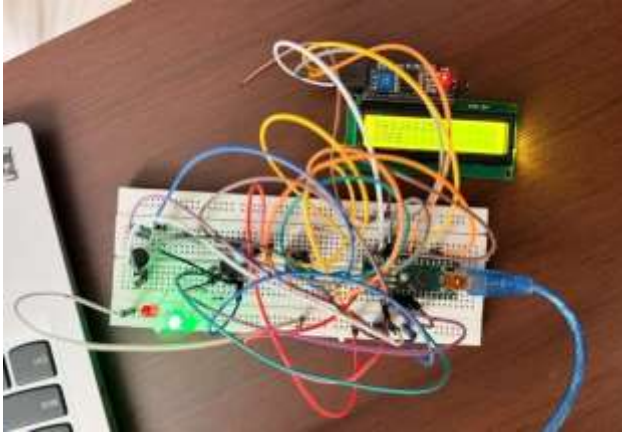


Fig.2. Hardware prototype showing the safe condition, with the green LED activated and the LCD displaying the 'SAFE' status when the detected noise level does not exceeds the adaptive threshold.

1. Signal acquisition and conditioning

The conditioned microphone signal is sampled by the Arduino Nano and transmitted to LabVIEW. Before calculating sound-level and spectral quantities, the acquired samples are checked for offset and scaled according to the calibration relationship established with a reference sound-level meter. Calibration is essential because the electret microphone and amplifier provide an electrical representation of sound rather than a directly traceable sound-pressure-level measurement.

1. RMS and sound-level estimation

For a window containing N acquired samples $x[n]$, the RMS magnitude is calculated as $x_RMS = \sqrt{\frac{1}{N} \sum_{n=0}^{N-1} x^2[n]}$ (1)

The calibrated sound level is then obtained from the RMS quantity using the experimentally determined microphone/conditioning calibration relationship. A generic logarithmic representation is

$$L = 20 \log_{10}(V_RMS / V_ref) + C_cal \quad (2)$$

where V_RMS is the measured electrical RMS value, V_ref is the selected reference value and C_cal is the calibration offset obtained from comparison with the reference meter. The exact calibration constants should be reported with the final experimental results.

2 Frequency-domain analysis

FFT analysis is used to transform the sampled waveform from the time domain into the frequency domain. For an N -point sample sequence, the discrete Fourier transform is

$$X[k] = \sum_{n=0}^{N-1} x[n] \exp(-j2\pi kn/N) \quad (3)$$

The magnitude spectrum is examined to determine dominant frequency components and the distribution of spectral energy. Rather than assigning a source from one frequency value alone, the proposed classification stage considers dominant frequency, spectral energy distribution and signal magnitude. This is intended to reduce errors caused by overlapping frequency content among traffic, horns, speech, music and construction sounds.

IV. ADAPTIVE DETECTION AND SOURCE CLASSIFICATION

1. Adaptive background-noise threshold

A fixed threshold can generate repeated alarms when the ambient background level changes between locations or time periods. The proposed approach first estimates the background level over short observation windows in which no target event is detected. Let μ_B and σ_B denote the estimated mean and standard deviation of the background level. A practical adaptive threshold is defined as

$$T_ad = \mu_B + k\sigma_B \quad (4)$$

where k is a sensitivity coefficient selected during validation. When the measured level exceeds T_ad for a specified minimum duration, the system flags a potential noise event. The coefficient and persistence time should be tuned using recorded background and event samples. This makes the adaptive mechanism testable and avoids presenting an arbitrary fixed threshold as a universal environmental limit.

2. Exposure and event metrics

The monitoring dashboard is designed to report the equivalent continuous sound level, maximum observed level and duration of threshold violation. For a time-varying level $L(t)$, the equivalent level over duration T can be expressed as

$$L_eq = 10 \log_{10} \left[\frac{1}{T} \int_0^T 10^{(L(t)/10)} dt \right] \quad (5)$$

These metrics complement instantaneous readings by

describing the accumulated acoustic condition over a selected measurement interval.

1. Noise-source classification

The classification module assigns an observed event to representative categories: traffic/engine, horn, speech, music and construction. The initial decision logic uses FFT-derived spectral characteristics together with signal magnitude. The frequency ranges are treated as indicative rather than exclusive because real environmental sources overlap in frequency. During validation, each class should be represented by repeated recordings under controlled and semi-realistic conditions. The classifier should be evaluated using a confusion matrix and class-wise precision, recall and F1-score in addition to overall accuracy.

Feature	Purpose in the proposed system
RMS level	Estimate signal magnitude and support calibrated dB calculation
Dominant frequency	Identify strong tonal or low-frequency components
Spectral energy distribution	Distinguish broadband and concentrated spectral patterns
Leq / Lmax	Characterize exposure and peak event level
Violation duration	Separate short peaks from sustained events

Table 1. Signal features and their intended role in monitoring and classification.

V. LABVIEW IMPLEMENTATION

The LabVIEW application forms the central processing and user-interface layer. The Arduino communicates through the USB serial interface, and the received samples are arranged into analysis windows. The front panel is designed to display the time-domain waveform, calibrated sound level, FFT spectrum, event classification, adaptive threshold and alert status. The application also supports logging of measurements for later comparison and trend analysis.

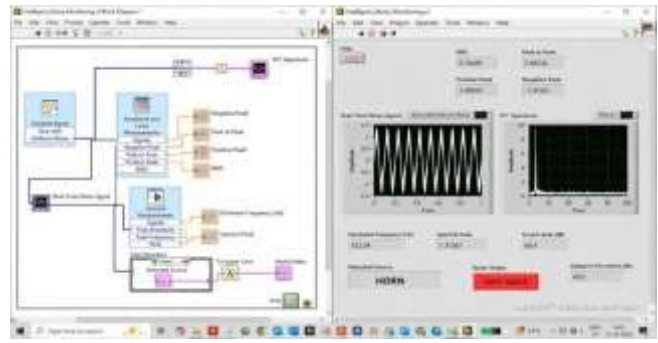


Fig. 3. LabVIEW validation for a horn sound. The measured sound level is 68.4 dB, exceeding the adaptive threshold of 60 dB and consequently triggering the "HIGH NOISE" status. FFT analysis gives a dominant frequency of 512.04 Hz, and the system classifies the detected source as "HORN".

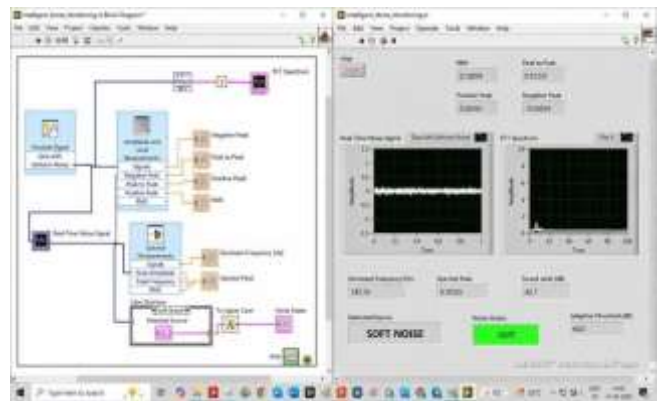


Fig.4. LabVIEW validation under a soft-noise condition. A sound level of 42.7 dB is measured against an adaptive threshold of 60 dB, resulting in a "SAFE" status. The FFT-based analysis gives a dominant frequency of 183.76 Hz, and the system classifies the input as "SOFT NOISE".

The processing sequence is: (1) acquire serial samples; (2) remove or account for DC offset; (3) calculate RMS; (4) convert the RMS value to calibrated sound level; (5) compute FFT and spectral features; (6) estimate the current background level and update the adaptive threshold; (7) calculate Leq, Lmax and violation duration; (8) classify the event; and (9) update the dashboard, alerts and log file. This sequence keeps acquisition, signal processing and decision logic traceable within a single LabVIEW environment.

VI. EXPERIMENTAL VALIDATION AND DISCUSSION

1. LabVIEW Functional Validation

The developed LabVIEW interface was first validated using different input-noise conditions to verify the

Table 2. Signal features and their intended role in monitoring and classification.

Test condition	RMS	Peak-to-Peak	Dominant frequency (Hz)	Spectral peak	Sound level (dB)	Adaptive threshold (dB)	Detected source	Status
Soft noise	0.12854	0.51237	183.76	0.10325	42.7	60.0	Soft Noise	SAFE
Horn	0.76289	2.96236*	512.04	1.31567	68.4	60.0	Horn	HIGH NOISE

• From the displayed positive and negative peaks:
 $VP-P=0.26183-(-0.25054)=0.51237V_{(P-P)}=0.26183-(-0.25054)=0.51237$
 for the soft-noise case.

1. For the horn case:

$VP-P=1.48954-(-1.47281)=2.96235V_{(P-P)}=1.48954-(-1.47281)=2.96235$
 which corresponds to the displayed value of approximately **2.9626** in your LabVIEW panel.

The two test cases demonstrate that the developed LabVIEW framework responds differently to low- and high-level acoustic inputs. For the soft-noise condition, the measured sound level of **42.7 dB** is below the displayed adaptive threshold of **60 dB**, resulting in a **SAFE** indication. The system identifies the input as soft noise, with a dominant spectral component of **183.76 Hz**.

For the horn test case, the measured sound level increases to **68.4 dB**, exceeding the displayed adaptive threshold of **60 dB**. Consequently, the system changes the noise status to **HIGH NOISE** and identifies the input as **HORN**. The dominant frequency of **512.04 Hz** and higher spectral peak provide frequency-domain characteristics used by the classification logic.

signal-processing, spectral-analysis, adaptive-threshold and source-classification functions. The system simultaneously provides time-domain measurements, frequency-domain analysis, sound-level estimation, adaptive threshold comparison and noise-status classification.

1. Adaptive Threshold Validation

The system uses an adaptive threshold rather than treating one fixed sound level as universally dangerous. The principle is:

$T_{ad} = \mu_B + k\sigma_B$ where:

T_{ad} = adaptive detection threshold

1. μ_B = estimated background-noise level
2. σ_B = variation in background noise
3. k = sensitivity factor

The current noise level is then compared with this threshold: $L_{current} > T_{adaptive} \Rightarrow \text{ALERT}$ and $L_{current} \leq T_{adaptive} \Rightarrow \text{SAFE}$

Table 3 Adaptive threshold validation results.

2. Hardware Alert Validation

The hardware prototype demonstrated the physical alert mechanism through the activation of the red LED and corresponding ALERT indication on the LCD. This provides a direct visual indication of excessive noise at the sensing unit and complements the software-based monitoring interface.

VII. DISCUSSION

The proposed system occupies an intermediate point between basic threshold-based noise meters and

computationally intensive environmental sound classification systems. Its emphasis is on a transparent, low-cost signal-processing pipeline that can be implemented and inspected in LabVIEW. The system is therefore suitable for demonstrating how acoustic acquisition, calibration, spectral analysis, adaptive detection and event classification can be integrated into a single monitoring workflow.

Compared with a fixed-threshold alarm, adaptive thresholding is intended to make event detection more dependent on the local acoustic background. Compared with a level-only monitor, FFT-based features add information about the type of acoustic event. Compared with deep-learning environmental sound classifiers, the proposed method deliberately uses a lightweight feature-based approach so that the prototype remains understandable and computationally modest. These are system-design distinctions; quantitative superiority should not be claimed unless supported by the completed experiments.

VIII. CONCLUSION

A low-cost LabVIEW-based environmental noise monitoring and source-classification framework has been developed using an electret microphone, LM358 signal conditioning and an Arduino Nano acquisition interface. The proposed software pipeline combines RMS-based sound-level estimation, FFT analysis, adaptive background-noise thresholding, Leq/Lmax metrics, event-duration monitoring, source classification, alerts and logging. The hardware prototype has been integrated, while final calibration and experimental validation remain to be completed. The completed evaluation will establish measurement error against a reference sound-level meter and quantify classification performance using accuracy, precision, recall, F1-score and a confusion matrix. The work is intended as a practical, low-cost and transparent platform for environmental noise monitoring and as a foundation for future expansion toward larger datasets, improved classifiers and connected monitoring.

IX. FUTURE WORK

Future development will focus on reference-meter calibration, expansion of the noise-source dataset, improved feature selection, and evaluation of lightweight machine-learning classifiers where rule-based classification is insufficient. The hardware can subsequently be migrated to a compact PCB, and optional IoT connectivity can be added for remote monitoring. These extensions can improve scalability without changing the core acquisition and LabVIEW processing architecture.

Acknowledgements. The authors acknowledge the support of the School of Electronics and Instrumentation Engineering, Vellore Institute of Technology, Vellore, India, for providing the academic and laboratory environment for this work.

Funding. No external funding was used for the development of the prototype.

Data availability. Experimental data will be made available by the authors upon reasonable request after completion of the validation campaign.

Author contribution. All authors contributed to system design, hardware integration, software development, testing planning and manuscript preparation.

REFERENCES

1. World Health Organization, Environmental Noise Guidelines for the European Region, WHO Regional Office for Europe, Copenhagen, 2018. <https://www.who.int/publications/i/item/9789289053563>
2. A. Hill, P. Prince, C. Snaddon, C. Doncaster, and A. Rogers, "AudioMoth: A low-cost acoustic device for monitoring biodiversity and the environment," *HardwareX*, vol. 6, p. e00073, 2019. doi: 10.1016/j.ohx.2019.e00073.
3. P. Prince, A. Hill, E. Piña Covarrubias, P. Doncaster, J. L. Snaddon, and A. Rogers, "Deploying acoustic detection algorithms on low-cost, open-source acoustic sensors for environmental monitoring," *Sensors*, vol. 19, no. 3, p. 553, 2019. doi: 10.3390/s19030553.
4. L.-J. Chen, S. Saraswat, F.-S. Ching, C.-Y. Su, H.-L. Huang, and W.-C. Pan, "Development and implementation of EcoDecibel: A low-cost and IoT-based device for noise measurement," *Ecological*

- Informatics, vol. 85, p. 102968, 2025. doi: 10.1016/j.ecoinf.2024.102968.
5. A. Bansal and N. K. Garg, "Environmental sound classification: A descriptive review of the literature," *Intelligent Systems with Applications*, vol. 16, p. 200115, 2022. doi: 10.1016/j.iswa.2022.200115.
6. W. Mu, B. Yin, X. Huang, J. Xu, X. Du, et al., "Environmental sound classification using temporal-frequency attention based convolutional neural network," *Scientific Reports*, vol. 11, p. 21552, 2021. doi: 10.1038/s41598-021-01045-4.
7. K. M. A. Kumar and T. C. Manjunath, "A novel design & development of adaptive noise cancellation in machines using LABVIEW," in *Proc. IEEE International Conference on Power, Control, Signals and Instrumentation Engineering (ICPSCI)*, pp. 1799–1804, 2017. doi: 10.1109/ICPSCI.2017.8392024.
8. S. Selvendran, V. Karthik, A. V. Mahanta, and V. V. Vyas, "Detecting and monitoring noise pollution with Arduino Uno: An innovative approach," *Proceedings on Engineering Sciences*, vol. 7, pp. 2645–2654, 2025. doi: 10.24874/PES07.04A.026.
9. F. Alías, J. C. Socoró, and X. Sevillano, "A review of physical and perceptual feature extraction techniques for speech, music and environmental sounds," *Applied Sciences*, vol. 6, no. 5, p. 143, 2016. doi: 10.3390/app6050143.
10. S. Abdoli, P. Cardinal, and A. Lameiras Koerich, "End-to-end environmental sound classification using a 1D convolutional neural network," *Expert Systems with Applications*, vol. 136, pp. 252–263, 2019. doi: 10.1016/j.eswa.2019.06.040.
11. K. J. Piczak, "Environmental sound classification with convolutional neural networks," in *Proc. IEEE 25th International Workshop on Machine Learning for Signal Processing (MLSP)*, pp. 1–6, 2015. doi: 10.1109/MLSP.2015.7324337.
12. J. Salamon and J. P. Bello, "Deep convolutional neural networks and data augmentation for environmental sound classification," *IEEE Signal Processing Letters*, vol. 24, no. 3, pp. 279–283, 2017. doi: 10.1109/LSP.2017.2657381.
13. J. Salamon, C. Jacoby, and J. P. Bello, "A dataset and taxonomy for urban sound research," in *Proc. 22nd ACM International Conference on Multimedia*, pp. 1041–1044, 2014. doi: 10.1145/2647868.2655045.
14. S. K. Prabhakar, Y.-G. Ju, and D.-O. Won, "HM-GDM: Hybrid measures and graph-dependent modeling for environmental sound classification," *International Journal of Computational Intelligence Systems*, vol. 17, p. 212, 2024. doi: 10.1007/s44196-024-00622-5.
15. M. Goulão, L. Bandeira, B. Martins, et al., "Training environmental sound classification models for real-world deployment in edge devices," *Discover Applied Sciences*, vol. 6, p. 166, 2024. doi: 10.1007/s42452-024-05803-7.