

Amplitude-Based Statistical Filtering Method for Resonance Localization in Low-Cost Acoustic Sensing Systems

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Submitted : June 4, 2026 | Accepted : June 24, 2026 | Published : July 5, 2026

Abstract: Acoustic resonance experiments using closed organ pipes are widely used to study the relationship between sound frequency, wavelength, and air-column length. However, low-cost sensor-based systems often produce unstable acoustic signals contaminated by environmental noise, amplitude fluctuations, and sensor-response variability, making resonance identification difficult. This study aims to develop and evaluate an amplitude-based statistical filtering method to improve signal stability and determine the fundamental resonance position more accurately. The proposed method was evaluated using a closed organ pipe experiment integrated with an acoustic sensor and microcontroller-based data acquisition system. Acoustic signals were processed using amplitude-based statistical filtering to extract dominant resonance responses and improve resonance localization. Statistical evaluation was conducted to analyze signal stability and measurement accuracy. The results showed that the filtering process reduced the standard deviation from 9.24 cm in the raw dataset to 6.72 cm in the final resonance candidates, indicating improved resonance localization stability. The experimental resonance length obtained after filtering was 16.12 cm, while the theoretical resonance length was 16.75 cm, resulting in a relative error of 3.76%. These findings demonstrate that the proposed filtering method can improve resonance detection accuracy using a simple, practical, and computationally efficient approach suitable for low-cost educational laboratory systems.

Keywords: Acoustic Resonance; Amplitude-Based Filtering; Closed Organ Pipe; Low-Cost Sensor System; Statistical Signal Analysis

INTRODUCTION

Sound waves are longitudinal mechanical waves generated by vibrating sources and propagating through a medium (Sahin et al., 2023). Their propagation characteristics are influenced by medium properties, with sound velocity in air reaching approximately 340–343 m/s at room temperature (Manela & Ben-Ami, 2024). A closed organ pipe resonance experiment is commonly used to analyze sound-wave characteristics through standing-wave formation inside the air column (Neimarlija & Arifović, 2023; Contreras & Volke-Sepúlveda, 2024). Under resonance conditions, the relationship between air-column length, wavelength, and sound frequency can be quantitatively analyzed to determine important physical parameters such as wavelength and sound velocity (Pratiwi et al., 2025). The advancement of digital technology has encouraged the use of microcontroller-based sensors and digital analysis systems in acoustic experiments (Gidion et al., 2023). Previous studies have demonstrated that Arduino-based sensor systems can provide practical and low-cost solutions for real-time monitoring and data acquisition in experimental applications (Lupitha & Haryono, 2022). Low-cost sensor systems offer practical advantages for educational laboratories because they are affordable, simple to implement, and suitable for environments with limited facilities (Heriard-Dubreuil et al., 2023). Previous studies have also demonstrated that microcontroller-based monitoring systems integrated with ultrasonic sensors can support efficient real-time data acquisition and experimental monitoring processes (Karjadi & Haryono, 2022). However, experimental data obtained from such systems are often contaminated by environmental noise, amplitude fluctuations, and signal instability caused by sensor limitations and air-column dynamics inside the tube (Enkhbat et al., 2024). These disturbances make resonance peaks difficult to identify accurately from raw experimental data.

Unstable measurements of sound intensity and frequency may reduce the reliability of experimental results (Lee et al., 2022). Noise-contaminated signals generally produce irregular data distributions, causing difficulties

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in determining resonance positions precisely. This issue becomes more significant when low-cost devices with limited measurement resolution are used (Komarizadehasl et al., 2022). In standing-wave experiments, clear and stable signals are required to properly analyze the relationship between physical variables and to ensure consistency between experimental and theoretical results (Guizzo et al., 2022). The motivation for this study emerged from the observation that resonance information is still contained within raw experimental data, although it is often masked by dominant noise and random fluctuations (Pawłowski et al., 2023). It is assumed that the dominant signal can be extracted using a simple signal-processing approach without requiring computationally complex methods (Liu et al., 2023). This approach is intended to emphasize data that represent resonance conditions while maintaining low computational complexity and implementation efficiency (Ramesh et al., 2022).

Previous studies have mainly focused on improving resonance accuracy through calibration methods or the use of high-specification instruments (Rashid, 2023). Although these approaches provide good measurement accuracy, they are not always suitable for educational laboratories with limited equipment and financial resources (Staacks et al., 2018). Several signal-processing methods such as moving average filtering, low-pass filtering, and Fast Fourier Transform (FFT) have also been widely applied to reduce noise and improve signal quality. Studies on sensor-based acquisition systems indicate that calibration can significantly improve measurement accuracy; nevertheless, additional filtering processes are still necessary to minimize noise and enhance signal precision (Septiana et al., 2024). Despite their effectiveness, these methods still present limitations related to computational complexity, implementation requirements, and suitability for low-cost microcontroller-based systems. Therefore, a simple statistical filtering approach is needed to improve signal stability and resonance identification accuracy without increasing system complexity (Junior et al., 2023). Accurate resonance-position determination is essential for understanding sound-wave concepts. Unclear and inconsistent experimental data may cause errors in interpreting the relationship between air-column length, frequency, and wavelength. Therefore, improving experimental data quality is important for effective physics learning and reliable analysis.

This research aims to develop and evaluate an Amplitude-Based Statistical Filtering Method by addressing the research question: How effectively can the proposed method improve signal stability and resonance identification accuracy in low-cost acoustic sensor systems? The method improves measurement consistency and resonance localization by extracting dominant acoustic responses. Unlike previous studies on resonance measurement accuracy and visualization, this study improves resonance-localization stability in low-cost acoustic sensing systems. The proposed amplitude-based statistical filtering method combines amplitude prioritization and statistical evaluation to reduce fluctuations and improve resonance identification reliability without requiring intensive signal processing techniques.

METHOD

This study employed an experimental method to evaluate the effectiveness of an amplitude-based filtering approach in improving the quality of acoustic data obtained from a closed organ pipe resonance experiment. The proposed method was developed based on concepts commonly applied in acoustic signal processing and digital data analysis for noise reduction and signal stabilization in sensor-based measurements (Gidion et al., 2023; Junior et al., 2023; Ramesh et al., 2022). The research focused on developing a simple and efficient filtering technique suitable for low-cost experimental systems used in educational laboratories. The experimental system consisted of a closed organ pipe, a fixed-frequency sound source, a microphone sensor, and a microcontroller equipped with an Analog-to-Digital Converter (ADC). The microphone converted acoustic waves into analog electrical signals, which were then transformed into digital amplitude data through the ADC. This system enabled real-time acquisition of acoustic signals in the form of numerical amplitude values.

Data collection was carried out by varying the air-column length gradually within a predetermined range. At each variation of the air-column length, the sound amplitude was recorded in ADC units. To improve measurement consistency and minimize random error, each measurement was repeated several times under the same experimental conditions. The resulting dataset consisted of paired values of air-column length and sound amplitude. The collected data were processed through several sequential stages. First, the characteristics of the raw data were identified by analyzing amplitude distribution, signal fluctuations, and noise levels. Second, the proposed filtering method using a simple statistical approach was applied to reduce the influence of noise. Signal filtering and noise reduction techniques are commonly applied in sensor-based measurement systems to improve signal reliability and minimize the influence of unwanted fluctuations during data acquisition (Lu et al., 2023). The filtering process was performed by selecting the top 10% highest amplitude values from each dataset as dominant resonance candidates. The 10% threshold was determined based on preliminary threshold evaluation by comparing several selection ranges. Lower thresholds produced fewer data points and increased the risk of eliminating valid resonance responses, while higher thresholds retained more noise components. Therefore, the 10% threshold was selected as a compromise between retaining dominant resonance information and minimizing noise contamination. Preliminary observations showed that threshold values below 10% produced fewer resonance

candidates and increased the possibility of removing valid resonance information. In contrast, threshold values above 10% retained more data points but increased the possibility of including noise components.

After filtering, the processed data were analyzed statistically using parameters such as mean value and standard deviation to evaluate signal stability and measurement consistency. The resonance position was determined from the concentration of dominant amplitude values indicating maximum resonance response. Finally, the experimental results were compared with theoretical resonance values to determine the accuracy of the proposed method and evaluate the measurement error between theoretical and experimental results. The overall procedure of this research is illustrated in Figure 1, which shows the stages of acoustic signal acquisition, raw-data analysis, amplitude-based filtering, statistical evaluation, and resonance-position determination.

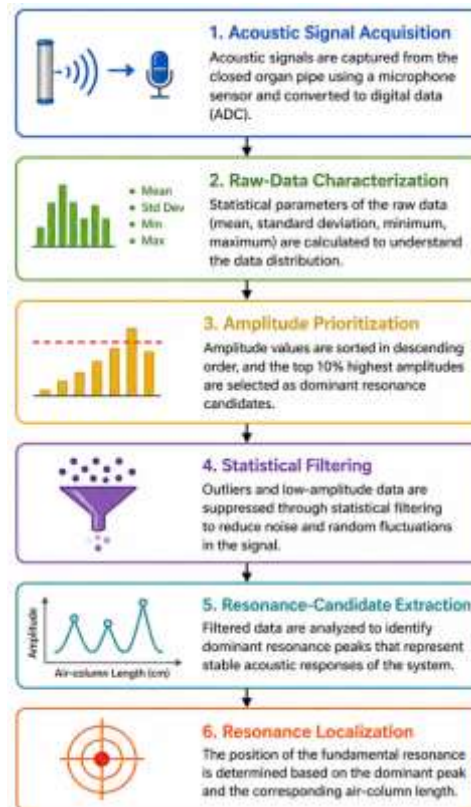


Figure 1. Conceptual workflow of the proposed filtering approach for resonance localization in low-cost acoustic sensing systems.

The proposed filtering method consists of several sequential stages, including acoustic signal acquisition, raw-data characterization, amplitude prioritization, statistical filtering, resonance-candidate extraction, and resonance localization. This structured process was designed to progressively suppress irregular fluctuations while preserving dominant resonance responses under unstable measurement conditions. While Figure 1 provides the overall conceptual framework of the proposed method, a more detailed computational procedure is required to describe the filtering process systematically. Therefore, the step-by-step implementation of the amplitude-based statistical filtering process is presented in Algorithm.

Algorithm: Amplitude-Based Statistical Filtering Procedure

Input: Raw acoustic dataset $D = \{L_i, A_i\}$
where L_i represents air-column length and A_i represents ADC amplitude value.

Output: Filtered resonance position L_r and signal stability parameters.

Step 1: Acquire acoustic signals from the microphone sensor and store the measured amplitude A_i with the corresponding air-column length L_i

Step 2: Arrange dataset D based on amplitude magnitude in descending order.

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Step 3: Determine the filtering threshold:

$$N_f = 0.1 \times N$$

Where N_f is the number of selected data points and N is the total number of measurements

Step 4: Select the top 10% highest amplitude values as dominant resonance candidate

Step 5: extract the corresponding air-column length values:

$$D_f = \{L_i, A_i | A_i \in \text{top } 10\%\}$$

Step 6: Calculate statistical parameters:

Mean resonance position:

$$\bar{L} = \frac{1}{n} \sum_{i=1}^n L_i$$

Standard deviation:

$$\sigma = \sqrt{\frac{\sum_{i=1}^n (L_i - \bar{L})^2}{n - 1}}$$

Step 7: Compare the filtered resonance position with theoretical resonance length.

Return: Final resonance localization result and stability evaluation.

The algorithm describes the computational procedure used to process acoustic signals and identify the resonance position from the acquired data. The implementation of this procedure requires an experimental system capable of collecting acoustic responses from the closed organ pipe. Therefore, the experimental setup used for acoustic signal acquisition is presented in Figure 2.

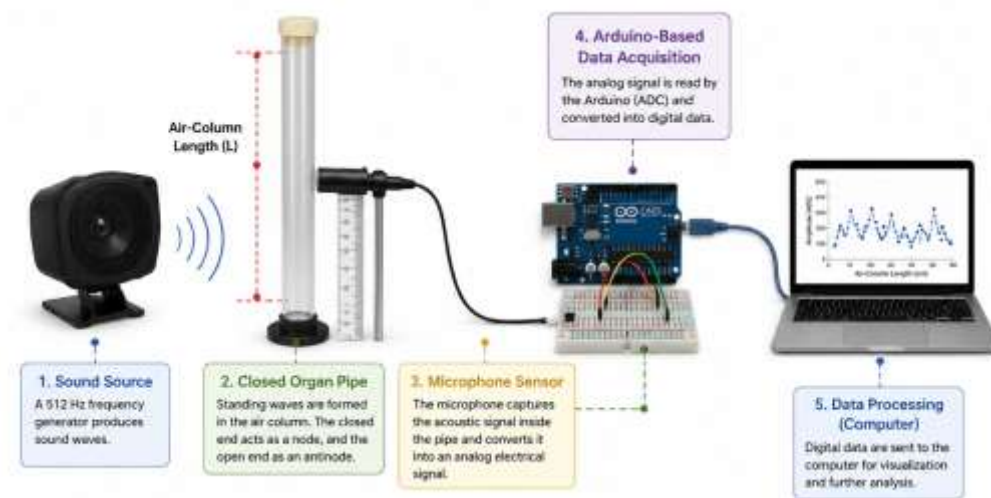


Figure 2. Experimental setup consisting of a closed organ pipe, microphone sensor, sound source, and Arduino-based data acquisition system.

The experimental setup was designed using low-cost and easily accessible components to support practical implementation in educational laboratory environments. The integration between the microphone sensor, Arduino-based acquisition system, and resonance tube enabled real-time collection of acoustic amplitude data.

Table 1. Comparison of Previous Studies and Proposed Study

Study	Focus	Method	Limitation
Iskandar & Pramudya (2024)	Resonance Measurement	Arduino + Visualization	No signal stabilization
Iskandar & Pramudya (2025)	Effective Length Analysis	Physical Analysis	No noise handling

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Study	Focus	Method	Limitation
Proposed Study	Resonance Localization Stability	Statistical Filtering	Low computational cost

Table 1 summarizes the differences between previous resonance studies and the proposed study. While previous approaches mainly focused on resonance measurement and accuracy improvement, this study emphasizes signal stability enhancement through a statistical filtering approach. The research positioning and contribution of the proposed approach are illustrated in Figure 3.



Figure 3. Research positioning of the proposed approach for improving resonance localization stability compared with previous studies.

RESULT

The experiment was conducted to evaluate the effectiveness of the proposed ADC-based amplitude filtering method in identifying the fundamental resonance position of a closed pipe system. Four experimental trials were performed in a single session using a 512 Hz excitation frequency. The raw data consisted of distance measurements (cm) and corresponding sound intensity values recorded in ADC units. The raw experimental data exhibited a wide distribution of sound intensity values across the entire air column range of 5–35 cm. The unfiltered dataset showed irregular fluctuations without a clearly distinguishable resonance peak. High ADC values appeared sporadically at multiple positions, indicating the influence of environmental noise, sensor sensitivity variation, and acoustic reflections within the tube. Consequently, direct identification of the fundamental resonance position from the raw data alone was not reliable. To minimize transient fluctuations and isolate dominant acoustic responses, amplitude filtering was applied to the acquired acoustic signals. The filtered results were subsequently analyzed to determine the clustering region corresponding to the fundamental resonance position. The distribution characteristics of the raw ADC amplitude values before filtering are presented in Figure 4.

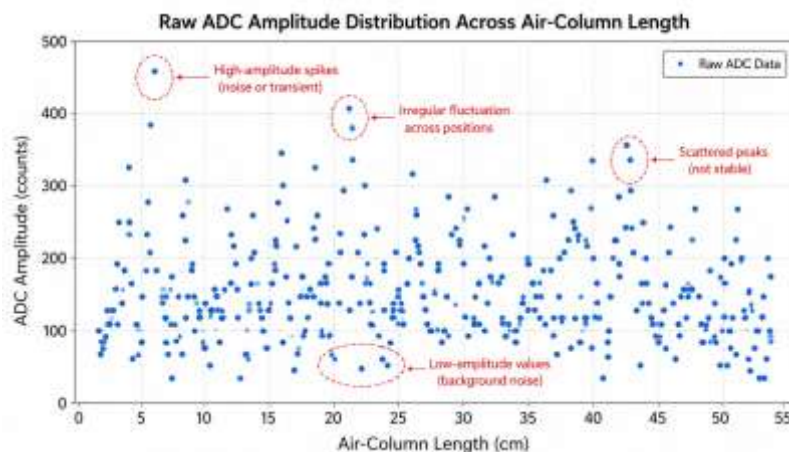


Figure 4. Distribution of raw ADC amplitude values across different air-column lengths before applying the filtering process.

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The irregular spread of high-amplitude values indicates that resonance-related responses cannot be directly distinguished from transient noise components without additional signal processing. The application of the 10% amplitude filtering method significantly reduced data dispersion and revealed a more concentrated distribution of resonance positions. For each trial, statistical parameters including the number of raw data points, the number of filtered data points, the mean resonance position, and the standard deviation were calculated. The summarized results of the four experimental trials are presented in Table 2.

Table 2. Statistical Characteristics of Raw Data

Parameter	Mean	Std Dev	Min	Max
ADC Amplitude	139.34	183.33	21	468
Distance (cm)	18.95	9.24	3.01	52.90

Table 2 shows the statistical characteristics of the raw acoustic signal. The amplitude signal exhibits a high standard deviation (183.33 ADC), which exceeds its mean value (139.34 ADC), indicating significant fluctuation and noise contamination in the measurement system. The large standard deviation observed in Table 1 suggests significant signal fluctuation. To further investigate the distribution of these fluctuations, the raw amplitude data were classified into several categories based on their intensity levels. The threshold ranges were determined empirically based on preliminary observations of ADC amplitude distribution.

Table 3. Distribution of Noise in Raw Acoustic Signal

Category	Criteria (ADC)	Number of Data	Percentage (%)
Background Noise	≤ 30	219	63.29
Intermediate Signal	31 – 300	44	12.72
High Spike / Clip-ping	> 300	83	23.99
Total	—	346	100

The selected threshold ranges were intended to separate dominant acoustic responses from low-intensity background noise and extreme transient spikes. Table 3 shows that 63.29% of the raw data falls within the background noise region (≤ 30 ADC), while 23.99% exhibits high-amplitude spikes (> 300 ADC). This indicates that the raw signal is heavily contaminated by noise and extreme fluctuations, justifying the need for digital filtering techniques. To further examine the characteristics of the raw acoustic signal, the distribution of ADC amplitude values was visualized using a histogram, as shown in Figure 5. The threshold values used for signal classification were determined empirically based on the observed amplitude distribution characteristics. This classification was intended to provide a clearer representation of signal fluctuation patterns and support subsequent filtering analysis.

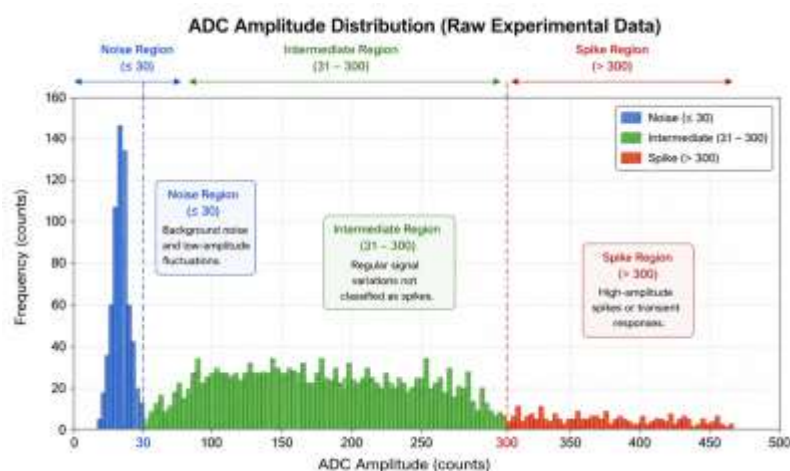


Figure 5. Comparison between raw acoustic data and filtered resonance candidates obtained using the amplitude-based filtering approach.

The histogram distribution also demonstrates that dominant resonance responses occupy only a limited portion of the overall dataset, supporting the use of selective statistical filtering for resonance localization. Figure 5 shows the distribution pattern of ADC amplitude values obtained from the raw experimental data. Most data points are

concentrated in the low-amplitude region, indicating dominant background noise components within the measurement system. Meanwhile, several isolated high-amplitude values appear as spikes, representing potential dominant acoustic responses associated with resonance conditions. The observed distribution pattern supports the signal categorization presented in Table 3 and confirms the presence of substantial signal fluctuation in the raw dataset. Based on these characteristics, a filtering procedure was subsequently applied to reduce noise influence and retain dominant resonance-related responses. The effectiveness of the progressive filtering process was then evaluated through statistical comparison at different filtering stages, as presented in Table 4.

Table 4. Progressive Statistical Comparison During Filtering Stages

Parameter	Raw Data	After Threshold Filter-ing	Final Resonance Candi-dates
Count	346	87	33
Mean (cm)	18.95	19.00	16.12
Std Dev (cm)	9.24	8.21	6.72
Min (cm)	3.01	4.47	4.47
Max (cm)	52.90	35.68	30.43

The remaining resonance candidates exhibit stronger spatial concentration around the expected resonance region, indicating improved localization consistency after filtering. Table 4 presents the progressive statistical changes observed during the filtering process. The number of data points decreased substantially from 346 in the raw dataset to 87 after threshold filtering and finally to 33 resonance candidates. A gradual reduction in data dispersion was also observed, as indicated by the decrease in standard deviation from 9.24 cm in the raw dataset to 8.21 cm after threshold filtering and further to 6.72 cm in the final resonance candidates. This reduction corresponds to a 27.27% decrease in overall data variability. In addition, the coefficient of variation (CV) decreased from 48.76% to 41.69%, indicating improved relative consistency in the processed data. The progressive reduction in both data count and variability suggests that the filtering process effectively removed irregular fluctuations while preserving dominant resonance-related responses. After progressively refining the dataset through filtering and resonance candidate selection, the final mean resonance length was obtained.

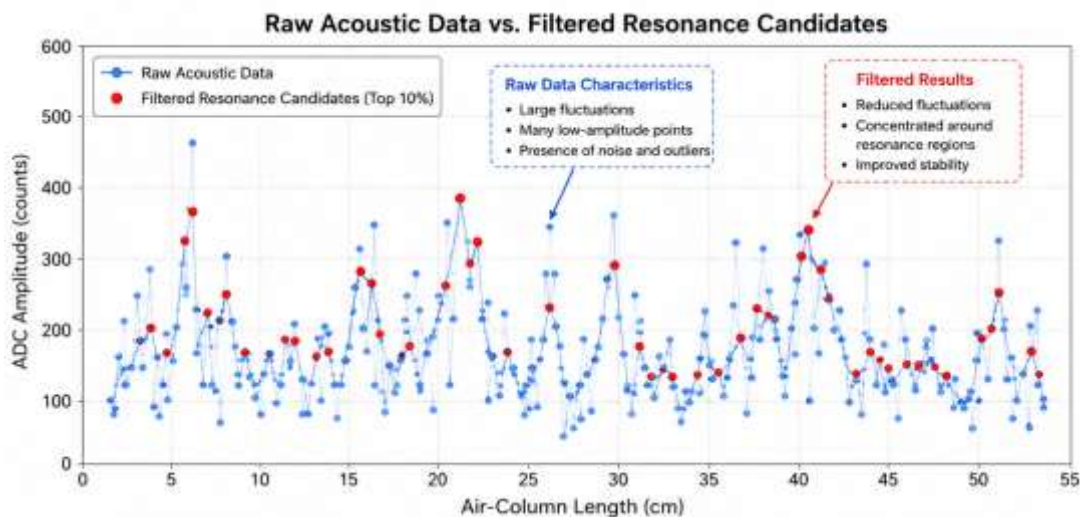


Figure 6. Identification of dominant resonance candidates after applying the statistical filtering process.

Figure 6 illustrates the difference between the raw acoustic measurements and the filtered resonance candidates. The filtered dataset exhibits a more concentrated distribution pattern with reduced fluctuation, indicating improved resonance localization stability.

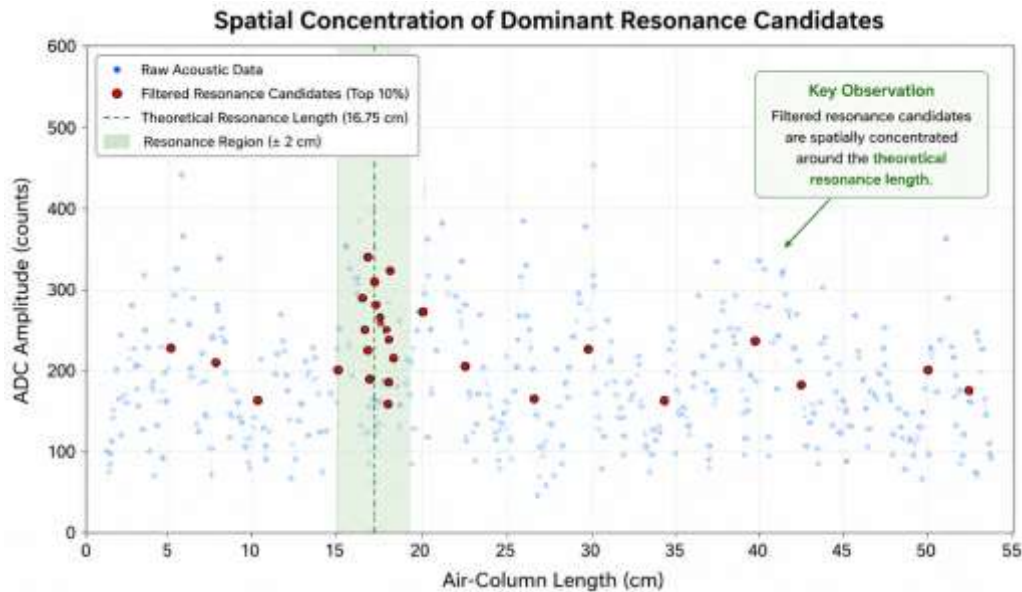


Figure 7. Evaluation of resonance position stability based on standard deviation reduction after filtering.

The clustering pattern shown in Figure 7 demonstrates that dominant resonance candidates are concentrated near the theoretical resonance region, supporting the validity of the proposed statistical filtering approach. To evaluate its agreement with theoretical prediction for a closed-end air column, a comparison between theoretical and experimental resonance lengths was performed, as presented in Table 5.

Table 5. Comparison Between Theoretical and Experimental Resonance Length

Parameter	Value
Frequency (Hz)	512
Speed of Sound (m/s)	343
Theoretical Length (cm)	16.75
Experimental Mean Length (cm)	16.12
Error (%)	3.76

The relatively small deviation between theoretical and experimental resonance lengths indicates acceptable measurement reliability for low-cost acoustic systems. Table 5 presents the comparison between theoretical prediction and experimental results for the determination of the fundamental resonance length in the closed pipe system. The theoretical resonance length for a 512 Hz sound source was calculated to be 16.75 cm, while the experimental mean length obtained from the final resonance candidates was 16.12 cm. The difference between these values resulted in a relative error of 3.76%, indicating that the experimental measurement closely follows the theoretical expectation. This result suggests that the proposed filtering approach is capable of preserving dominant resonance information while reducing the influence of noise and signal fluctuations.

DISCUSSIONS

The experimental results demonstrate that raw acoustic measurements obtained using low-cost sensors are highly susceptible to environmental noise and signal fluctuation (Niu & Luo, 2022). As shown in Tables 1 and 2, the amplitude distribution exhibits substantial variability, with a high standard deviation and a dominant proportion of background noise components. This confirms that direct identification of the resonance position from unfiltered ADC signals is unreliable due to transient spikes and ambient acoustic interference. The implementation of the proposed filtering method significantly improved resonance localization stability. As presented in Table 3, the progressive filtering process reduced the dataset from 346 raw data points to 33 final resonance candidates, accompanied by a 27.27% reduction in standard deviation (from 9.24 cm to 6.72 cm) and a decrease in the coefficient of variation from 48.76% to 41.69%. These results indicate that selective amplitude prioritization effectively suppresses irregular fluctuations while preserving dominant acoustic responses associated with standing-wave formation (Bao et al., 2020). Physically, the preserved dominant amplitude components represent the resonance condition where the air column supports the formation of a stable standing wave pattern (Gidion et al., 2023; Niu & Luo, 2022). At the fundamental resonance frequency, constructive interference between incident and reflected sound waves produces maximum acoustic energy accumulation, resulting in a significant increase in

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the detected sound amplitude (Niu & Luo, 2022; Wardana et al., 2019). Therefore, the concentration of high-amplitude signals after filtering indicates that the selected data points correspond to the actual resonance region rather than random acoustic disturbances. The reduction in signal dispersion also reflects improved consistency in detecting the pressure variation characteristics of the closed pipe resonance system.

The comparison between theoretical and experimental resonance lengths (Table 4) further validates the effectiveness of the proposed method. The theoretical fundamental resonance length for a closed pipe at 512 Hz is 16.75 cm, while the experimentally obtained mean length is 16.12 cm, yielding a relative error of 3.76%, which indicates good agreement between theoretical prediction and experimental measurement. This result suggests that the proposed filtering approach can provide reliable resonance localization while maintaining the simplicity and affordability required for low-cost educational laboratory systems (Wardana et al., 2019). Previous studies on resonance detection systems reported relative errors of 3.04% and 5.98% using Arduino-based resonance measurements under different water-level conditions (Iskandar & Pramudya, 2024), while a subsequent study achieved lower errors ranging from 1.33% to 0.24% through effective-length correction and Gaussian fitting analysis (Iskandar & Pramudya, 2025). Direct comparison of measurement accuracy alone should be interpreted carefully because the objectives of the studies differ. Earlier studies primarily emphasized calibration refinement and optimized experimental conditions to minimize absolute measurement error, whereas the present research focuses on evaluating the robustness of the proposed filtering approach under raw and noise-contaminated signal condition. Consequently, the slightly higher deviation can be attributed to environmental acoustic interference, sensor response variability, end correction effects at the open boundary, and the absence of temperature compensation during measurement. Despite this, the obtained error remains within an acceptable range and demonstrates stable resonance localization performance.

The findings highlight that the principal contribution of this study lies not merely in minimizing measurement error, but in enhancing signal stability and noise resilience through systematic filtering. The progressive reduction in dispersion and improvement in relative stability confirm that statistical amplitude-based selection can serve as a practical and computationally simple method for resonance detection in resource-limited laboratory settings. Overall, the study demonstrates that a low-cost Arduino-based acoustic measurement system can reliably identify the fundamental resonance position of a closed pipe system while maintaining measurement consistency under noisy experimental conditions. To further highlight the positioning and contribution of the proposed study, a comparison with previous resonance-detection studies is presented in Table 6.

Table 6. Comparison between the proposed study and previous resonance-detection studies.

Study	Method	Main Focus	Error	Contribution
Iskandar & Pramudya (2024)	Visualization	Resonance visualization	3.04–5.98%	Arduino resonance monitoring
Iskandar & Pramudya (2025)	Gaussian fitting	Accuracy optimization	0.24–1.33%	Effective-length correction
Proposed Study	Progressive statistical filtering	Signal stability & robustness	3.76%	Noise-resilient resonance localization

Table 6 highlights that the proposed method contributes primarily to improving signal robustness and measurement consistency rather than focusing exclusively on error minimization (Gannot et al., 2016). This distinction is important because reliable resonance identification depends not only on achieving low error values but also on maintaining stable signal characteristics under experimental fluctuations. Therefore, to further evaluate the filtering performance, the reduction in signal dispersion across progressive filtering stages was examined using standard deviation analysis, as presented in Figure 8.

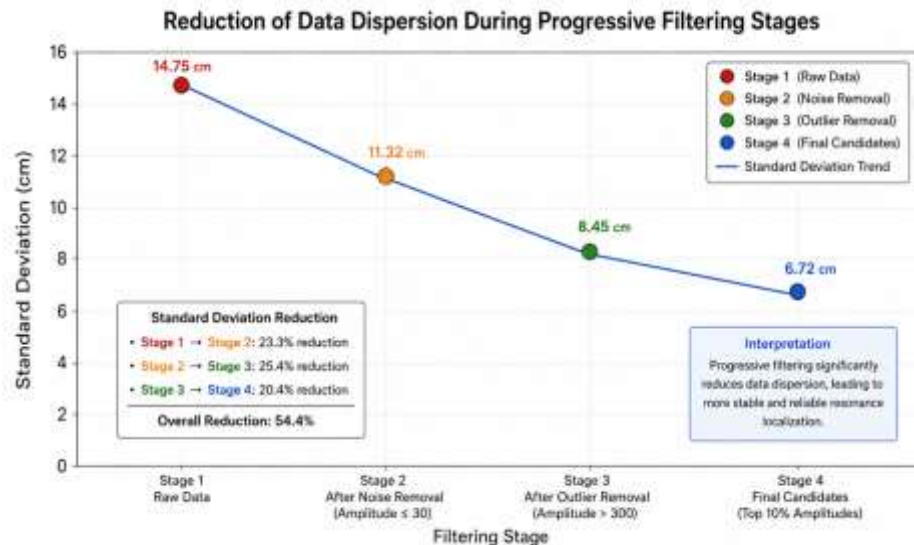


Figure 8. Reduction of data dispersion during progressive filtering stages measured using standard deviation.

Figure 8 visually confirms the progressive convergence of resonance candidates throughout the filtering stages. The decreasing variability indicates that the filtering process effectively concentrates dominant acoustic responses around the resonance region while suppressing random fluctuations and background noise. The gradual decrease in standard deviation values suggests that the filtering process effectively reduces random fluctuations and suppresses noise components in the measured acoustic signal (Lu et al., 2023). By progressively removing anomalous amplitude variations, the method retains more representative signal characteristics and improves the reliability of resonance-position determination. These findings support the effectiveness of the proposed method in enhancing measurement robustness for low-cost acoustic sensing systems.

Despite the improved resonance localization performance, several limitations of the proposed method should be considered. The current filtering approach relies primarily on amplitude-based selection; therefore, signals with high amplitude caused by unexpected noise sources may potentially be identified as resonance candidates. In addition, the experimental validation was limited to a fixed frequency and a specific low-cost acoustic sensor configuration, which may affect the generalization of the method under different acoustic conditions. Future studies should integrate frequency-domain analysis, adaptive threshold selection, and broader experimental variations to further improve the robustness and applicability of the proposed method (Bao et al., 2020; Gannot et al., 2016).

The contribution of this study extends beyond resonance-length estimation accuracy by demonstrating that reliable resonance localization can be achieved using a simple statistical filtering strategy without requiring computationally intensive signal-processing algorithms. The proposed method demonstrates that resonance localization can be stabilized without requiring complex digital signal-processing algorithms. This capability is particularly beneficial for educational laboratories and low-cost experimental platforms where computational resources and sensor quality are limited.

CONCLUSION

Addressing the challenge of unstable resonance identification in low-cost acoustic sensor systems, this study demonstrates that amplitude-based statistical filtering can reduce the influence of environmental noise, signal fluctuation, and unstable amplitude distribution in closed organ pipe experiments. The proposed amplitude-based statistical filtering method successfully improved signal consistency by reducing irrelevant fluctuations and emphasizing dominant resonance responses. The filtering process reduced the standard deviation of resonance-position data from 9.24 cm to 6.72 cm, indicating improved stability and more selective resonance detection. The experimental results also showed good agreement with theoretical calculations. The theoretical resonance length for a 512 Hz excitation frequency was 16.75 cm, while the experimental result obtained after filtering was 16.12 cm, resulting in a relative error of 3.76%. These findings indicate that the proposed method is capable of identifying the fundamental resonance position with acceptable accuracy using a simple and computationally efficient approach. Beyond numerical improvements, the proposed approach demonstrates that reliable resonance identification can be achieved through a simple statistical approach without requiring complex signal-processing algorithms. The findings highlight the potential of amplitude-based analysis for improving the reliability of low-cost acoustic sensing systems, particularly in educational laboratory environments where accessibility and computational efficiency are important.

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The main contribution of this research lies in the development of a practical filtering approach that can improve acoustic signal quality without requiring complex digital signal processing techniques or expensive instrumentation. This method is particularly beneficial for educational laboratories and low-cost experimental systems where hardware limitations often affect measurement quality. The proposed approach also demonstrates that simple statistical filtering can enhance the reliability of resonance experiments while maintaining implementation simplicity. However, this study still has several limitations. The filtering process was based only on amplitude selection and did not incorporate advanced frequency-domain analysis such as Fast Fourier Transform (FFT) or adaptive digital filtering methods. In addition, external environmental noise, sensor sensitivity variations, and the absence of temperature compensation may still influence measurement accuracy. Future studies are recommended to integrate real-time digital filtering techniques, higher-resolution sensors, and automatic environmental compensation systems to further improve resonance detection accuracy and signal stability. The integration of frequency-domain analysis may also provide more comprehensive acoustic characterization and improve the robustness of the proposed system for broader experimental applications.

ACKNOWLEDGMENT

This research was supported by the Institute for Research and Community Service (LPPM) of Institut Teknologi Batam through the Internal Lecturer Research Grant Program for the Even Semester of 2025–2026, as stipulated in the Rector Decree of Institut Teknologi Batam Number 039/SK/Rektor-ITEBA/VI/2026 and Research Contract Number 001/LPPM/KP-ITEBA/V/2026. The authors sincerely appreciate the financial support, laboratory facilities, and institutional assistance provided throughout the experimental implementation, data collection, and completion of this study. The authors also thank all parties who contributed directly or indirectly to the completion of this research.

REFERENCES

- Bao, Y., Tang, Z., & Li, H. (2020). Compressive-sensing data reconstruction for structural health monitoring: a machine-learning approach. *Structural Health Monitoring*, 19(1), 293–304. <https://doi.org/10.1177/1475921719844039>
- Contreras, V., & Volke-Sepúlveda, K. (2024). Enhanced standing-wave acoustic levitation using high-order transverse modes in phased array ultrasonic cavities. *Ultrasonics*, 138(December 2023). <https://doi.org/10.1016/j.ultras.2023.107230>
- Enkhbat, G., Xu, Y., Zhang, Y., & Xie, G. (2024). Acoustic Resonance Fast Detection Method of Harmonic Reducer Based on Support Vector Machine Algorithm. *Journal of Donghua University (English Edition)*, 41(3), 289–297. <https://doi.org/10.19884/j.1672-5220.202310003>
- Gannot, S., Vincent, E., Markovich-Golan, S., & Ozerov, A. (2016). A Consolidated Perspective on Multi-Microphone Speech Enhancement and Source Separation. *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, PP. <https://doi.org/10.1109/TASLP.2016.2647702>
- Gidion, G., Aftab, T., Reindl, L. M., & Rupitsch, S. J. (2023). Resonance phenomena in dielectric media: A review and comparison of acoustic and electromagnetic modes. *Journal of Advanced Dielectrics*, 13(4), 1–6. <https://doi.org/10.1142/S2010135X23410084>
- Guizzo, E., Marinoni, C., Pennese, M., Ren, X., Zheng, X., Zhang, C., Masiero, B., Uncini, A., & Communiello, D. (2022). L3Das22 Challenge: Learning 3D Audio Sources in a Real Office Environment. *ICASSP, IEEE International Conference on Acoustics, Speech and Signal Processing - Proceedings, 2022-May*, 9186–9190. <https://doi.org/10.1109/ICASSP43922.2022.9746872>
- Heriardi-Dubreuil, B., Besson, A., Cohen-Bacrie, C., & Thiran, J. P. (2023). Interpolation-Based Regularization for Speed of Sound Estimation in Layered Media. *IEEE International Ultrasonics Symposium, IUS*. <https://doi.org/10.1109/IUS51837.2023.10307144>
- Iskandar, F., & Pramudya, Y. (2024). A Comparative Study of Sound Resonance Using Arduino-Based Ultrasonic Sensors and Visualization Analysis with Python. *Jurnal Materi Dan Pembelajaran Fisika*, 14(2), 72. <https://doi.org/10.20961/jmpf.v14i2.93454>
- Iskandar, F., & Pramudya, Y. (2025). Studi Faktor Kualitas Resonansi Bunyi pada Pipa Organa Tertutup Menggunakan Panjang Efektif. *JIPFRI (Jurnal Inovasi Pendidikan Fisika Dan Riset Ilmiah)*, 9(1), 46–51. <https://doi.org/10.30599/jipfri.v9i1.4186>
- Junior, R. P., Rocha, C. A. F. Da, Chang, B. S., & Le Ruyet, D. (2023). A Generalized Two-Dimensional FFT Precoded Filter Bank Scheme With Low Complexity Equalizers in Time-Frequency Domain. *IEEE Access*, 11(September), 112414–112428. <https://doi.org/10.1109/ACCESS.2023.3323928>
- Karjadi, D. A., & Haryono, H. (2022). Objects Monitoring RADAR using Bluetooth Ultrasonic. *Sinkron*, 7(2), 359–366. <https://doi.org/10.33395/sinkron.v7i2.11347>



- Komarizadehasl, S., Mobaraki, B., Ma, H., Lozano-Galant, J. A., & Turmo, J. (2022). Low-Cost Sensors Accuracy Study and Enhancement Strategy. *Applied Sciences (Switzerland)*, 12(6). <https://doi.org/10.3390/app12063186>
- Lee, B., Yang, J., Cho, J. S., & Kim, S. (2022). A Low-Power Digital Capacitive MEMS Microphone Based on a Triple-Sampling Delta-Sigma ADC With Embedded Gain. *IEEE Access*, 10, 75323–75330. <https://doi.org/10.1109/ACCESS.2022.3188661>
- Liu, Z., Chen, L., Zhou, X., Jiao, Z., Guo, G., & Chen, R. (2023). Machine Learning for Time-of-Arrival Estimation With 5G Signals in Indoor Positioning. *IEEE Internet of Things Journal*, 10(11), 9782–9795. <https://doi.org/10.1109/JIOT.2023.3234123>
- Lu, P., Creagh, A. P., Lu, H. Y., Hai, H. B., Thwaites, L., & Clifton, D. A. (2023). 2D-WinSpatt-Net: A Dual Spatial Self-Attention Vision Transformer Boosts Classification of Tetanus Severity for Patients Wearing ECG Sensors in Low- and Middle-Income Countries. *Sensors*, 23(18). <https://doi.org/10.3390/s23187705>
- Lupitha, M., & Haryono, H. (2022). Prototype of movement monitoring Objects using Arduino Nano and SMS Notifications. *Sinkron*, 7(2), 601–610. <https://doi.org/10.33395/sinkron.v7i2.11413>
- Manela, A., & Ben-Ami, Y. (2024). Acoustic interaction of a finite body in a rarefied gas: Does sound reciprocity hold at non-continuum conditions? *Journal of Fluid Mechanics*, 999, 1–29. <https://doi.org/10.1017/jfm.2024.1003>
- Neimarlija, N., & Arifović, K. (2023). MATHEMATICAL AND NUMERICAL ANALYSIS OF THE RELATIONSHIP AMONG THE LOSCHMIDT CONSTANT, THE AVOGADRO CONSTANT, AND THE SPEED OF SOUND IN REAL GASES AT DIFFERENT THE pV THERMODYNAMIC PROPERTIES. *Mašinstvo*, 20(1), 19–29. <https://doi.org/10.62456/jmem.2023.01.019>
- Niu, Z., & Luo, D. (2022). Measurement of the Velocity of Sound Through Resonance in Air Columns as a Homemade Experiment. *The Physics Teacher*, 60, 114–116. <https://doi.org/10.1119/5.0023835>
- Pawłowski, E., Szlachta, A., & Otomański, P. (2023). The Influence of Noise Level on the Value of Uncertainty in a Measurement System Containing an Analog-to-Digital Converter. *Energies*, 16(3). <https://doi.org/10.3390/en16031060>
- Staacks, S., S Hütz, H Heinke, & C Stampfer. (2018). *Physics Education Advanced tools for smartphone-based experiments: phyphox*. <http://192.168.2.113>
- Pratiwi, I., Nugroho, H. S., Putri, S. A., Chen, D., Suryani, R., & Al-Hakim, R. R. (2025). Cross-platform Data Visualization of Acoustic Phenomena in Open and Closed Pipe Resonance Using Python and Microsoft Excel. *J. Aceh Phys. Soc*, 14(4), 28–36. <https://doi.org/10.24815/jacps.v14i4.47388>
- Ramesh, G., Logeshwaran, J., Gowri, J., & Mathew, A. (2022). the Management and Reduction of Digital Noise in Video Image Processing By Using Transmission Based Noise Elimination Scheme. *Ictact Journal on Image and Video Processing*, 9102(13), 1. <https://doi.org/10.21917/ijivp.2022.0398>
- Rashid, Dr. K. M. J. (2023). Optimize the Taguchi method, the signal-to-noise ratio, and the sensitivity. *International Journal of Statistics and Applied Mathematics*, 8(6), 64–70. <https://doi.org/10.22271/math.2023.v8.i6a.1406>
- Sahin, M. A., Ali, M., Park, J., & Destgeer, G. (2023). Fundamentals of acoustic wave generation and propagation. In *Acoustic Technologies in Biology and Medicine*. <https://doi.org/10.1002/9783527841325.ch1>
- Septiana, R., Deosa P. Caniago, & Harun Kurniawan. (2024). Evaluasi dan Kalibrasi Data Akuisisi Temperatur Berbasis Arduino dan MAX31855. *Jurnal Elektronika Dan Otomasi Industri*, 11(2), 621–627. <https://doi.org/10.33795/elkolind.v11i2.5250>
- Wardana, A., Prajitno, G., Indrawati, S., & Suyatno. (2019). Effect of amount and pipe size on resonance frequency. *Journal of Physics: Conference Series*, 1153(1). <https://doi.org/10.1088/1742-6596/1153/1/012005>