https://doi.org/10.65646/3cp3es20dpp1t129

Echo-Window Sensitivity of Spectral Features in Ultrasonic Backscatter Characterization of PE and PMMA Microplastics

Nethruwan Pathirana, U.S.Premarathne
The Department of Electrical and Computer Engineering
The Open University of Sri Lanka
Nawala-Nugegoda, Sri Lanka
S22004252@ousl.lk, uspre@ou.ac.lk

Abstract*— Ultrasonic backscatter provides a non-destructive approach for characterizing microplastic particles; however, the spectral features extracted from an echo can depend on the signal segment selected for analysis. This study investigates the sensitivity of polyethylene (PE) and poly(methyl methacrylate) (PMMA) spectral-feature differences to echo-analysis window length using a publicly available high-frequency ultrasonic backscatter dataset. Signals sharing a common 50-µm size label were analyzed using peak-centered windows of 64, 128, 256, and 384 samples. After mean removal and Hamming tapering, spectral centroid, spectral spread, and normalized spectral entropy were extracted from the Fourier-domain representation. Spatially neighboring measurements were grouped before statistical comparison to reduce the influence of repeated local observations. The results show clear feature-dependent window sensitivity. The PE–PMMA centroid difference remained comparatively stable, changing by only about 3.2% between the shortest and longest windows, whereas the spectral-spread difference increased by approximately 115%. Spectral entropy also showed substantial but non-monotonic variation with window length. These findings demonstrate that echo-analysis window selection is an important digital signal processing parameter and should be considered when evaluating the robustness and reproducibility of ultrasonic spectral features for microplastic characterization.

Keywords*— Microplastics, Ultrasonic backscatter, Digital signal processing, Spectral Centroid, Spectra, Window sensitivity

I. Introduction

Microplastic contamination has become an increasing concern in aquatic environments, creating a need for reliable methods to detect and characterize small plastic particles in water. Conventional techniques such as Fourier-transform infrared (FTIR) and Raman spectroscopy provide valuable polymer-specific information but can require laboratory-based sample preparation, specialized instrumentation, and considerable analysis time [1]–[3]. These practical constraints have encouraged investigation of complementary sensing techniques that may support faster and potentially non-destructive microplastic characterization.

Ultrasonic sensing provides an alternative approach by analyzing acoustic signals backscattered from particles. The interaction between an incident ultrasonic wave and a particle produces echo characteristics that can be examined in both the time and frequency domains. Recent work by Zarrabi *et al.* demonstrated that high-frequency ultrasonic backscatter contains information useful for microplastic material identification and size estimation, including information represented by temporal and spectral features [4]. Such results indicate that ultrasonic backscatter has potential as a complementary method for microplastic characterization.

However, spectral features obtained from an ultrasonic echo depend not only on the measured signal but also on how the signal is processed. In particular, the length of the echo-analysis window determines the portion of the waveform included in the Fourier analysis. Changing this window may alter the contribution of the principal echo and surrounding oscillations, potentially affecting the calculated spectral descriptors. Consequently, feature differences attributed to different materials should also be examined for their sensitivity to window selection.

This study investigates the sensitivity of spectral-feature differences between polyethylene (PE) and poly(methyl methacrylate) (PMMA) ultrasonic backscatter signals to echo-analysis window selection. A secondary analysis is performed using the publicly available labeled ultrasonic dataset reported by Zarrabi et al. [4]. PE and PMMA signals sharing a common size label are evaluated using analysis windows of 64, 128, 256, and 384 samples. Spectral centroid, spectral spread, and normalized spectral entropy are extracted following peak-centered windowing and Fourier analysis. Rather than optimizing classification performance, the study examines whether PE–PMMA spectral separation remains consistent across window lengths, thereby assessing the robustness of these interpretable spectral features to analysis-window selection.

II. Related Work

A. Existing Microplastic Characterization Methods

Microplastic characterization typically involves a combination of visual, spectroscopic, and chemical techniques to determine particle morphology and polymer composition. Fourier-transform infrared (FTIR) and Raman spectroscopy are widely used because molecular vibrational signatures enable identification of different polymer types [5]. Nevertheless, spectroscopic analysis can involve sample preparation, specialized instrumentation, and considerable measurement and processing effort, particularly when large numbers of particles must be examined [2], [5]. Recent reviews have therefore highlighted growing interest in methods that can complement established laboratory techniques and support faster or in-situ measurements in aquatic environments [2], [3].

The diversity of microplastics further complicates detection because particle size, shape, composition, and surrounding medium can influence the measured response [3]. Consequently, no single measurement approach addresses all characterization requirements. Emerging sensing strategies are therefore being investigated to obtain particle-related information through alternative physical interactions [2]. Within this context, acoustic sensing is of particular interest because particle–wave interactions can be examined through measurable backscattered signals, providing the basis for ultrasonic microplastic characterization.

B. Acoustic and Ultrasonic Approaches for Microplastic Characterisation

Acoustic techniques are increasingly being explored as complementary tools for microplastic detection and characterization. Photoacoustic imaging has been combined with deep-learning methods to obtain high-resolution particle information and classify microplastics according to morphological characteristics [6]. A related photoacoustic approach further demonstrated the integration of high-resolution imaging with feature-learning methods for microplastic surveillance, highlighting the potential of acoustically detected signals for automated particle analysis [7]. These techniques, however, generate acoustic responses through optical excitation and therefore differ from direct pulse-echo ultrasonic sensing.

Direct ultrasonic backscatter is more closely aligned with the current study because it provides direct access to particle-induced echo characteristics. High-frequency ultrasound has been used to acquire particle-specific backscattered signals and extract temporal and spectral information for microplastic material identification and size estimation [4]. In that work, a 40-MHz ultrasonic system was employed, and spectral centroid, spectral spread, and spectral entropy were identified as informative descriptors of material-related backscatter behavior. Acoustic techniques have also been explored for microplastic manipulation and separation, including the use of ultrasonic standing waves to trap plastic particles in flowing water [8]. Although these approaches involve different physical mechanisms and objectives, they collectively demonstrate the growing relevance of acoustic interactions in microplastic analysis. Among them, direct backscatter analysis is particularly pertinent to the present work because it provides a suitable basis for examining how signal-processing choices, especially echo-window selection, influence the extracted spectral characteristics.

C. Spectral Feature Extraction and Window Selection Effects

Frequency-domain analysis provides compact descriptors of information contained within ultrasonic echoes. Spectral centroid represents the energy-weighted location of the spectrum, spectral spread describes its dispersion, while spectral entropy characterizes the distribution of spectral energy. Such spectral information has shown value in ultrasonic backscatter characterization, including entropy-based assessment of scattering characteristics [9]. In microplastic analysis, spectral centroid, spread, and entropy have also been identified as informative features for material characterization [4].

The reliability of these descriptors is influenced by the signal segment used for spectral estimation. Finite-record windowing affects the spectral representation obtained through the discrete Fourier transform (DFT), including spectral leakage and frequency resolution [10]. In ultrasonic applications, the selected window duration determines how much of the principal echo and surrounding signal content contributes to the FFT; consequently, window size must be considered when obtaining spectral estimates from an echo [11]. Therefore, material-associated spectral differences may not remain unchanged when the analyzed echo duration is varied. This motivates the present evaluation of PE–PMMA spectral centroid, spread, and entropy across multiple peak-centered window lengths to determine their sensitivity to window selection.

Although spectral features have been used for ultrasonic microplastic characterization, their sensitivity to echo-analysis window length remains insufficiently examined. This is important because window-dependent features may affect the consistency of material-associated spectral differences. Therefore, this study evaluates PE–PMMA differences in spectral centroid, spectral spread, and spectral entropy across multiple peak-centered window lengths using signals with a common size label.

III. DATASET AND ANALYSIS METHODOLOGY

This study employs a secondary analysis of a publicly available ultrasonic backscatter dataset [12] to investigate the sensitivity of PE–PMMA spectral-feature differences to echo-analysis window length. The dataset accompanies the high-frequency ultrasonic micro-plastic characterization study reported in [4]. The analysis consists of controlled signal selection, peak-centered echo alignment, multi-window spectral processing, feature extraction, and group-level statistical comparison. The complete workflow is summarized in Fig. 1.

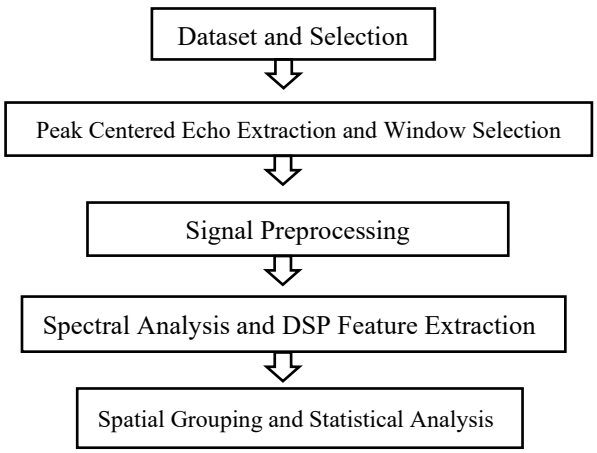


Figure 1. Overview of the Signal Processing Workflow Used in the Study

All signal-processing, feature-extraction, spatial-grouping and statistical analyses were implemented in MATLAB R2017a using custom scripts. The processing workflow included peak-centered segmentation, mean removal, Hamming windowing, FFT-based spectral analysis, and extraction of spectral centroid, spectral spread, and normalized spectral entropy.

A. Dataset and Signal Selection

The analysis was performed using the publicly available labeled ultrasonic backscatter dataset provided in [12], containing 8,045 signal traces from polyethylene (PE), poly(methyl methacrylate) (PMMA), glass, and steel microspheres. The processed dataset contains the ultrasonic waveform together with material-label, particle-size, and spatial-coordinate information. In the original study, measurements were obtained over 5×5 spatial regions, providing multiple backscatter traces from neighboring measurement locations [4].

To control particle-size variation in the PE–PMMA comparison, only signals sharing the 50-µm size label (Radius = 50 in the dataset) were retained. Here, Radius = 50 is treated as the size label supplied with the dataset rather than being independently interpreted as a physical radius measurement. This produced 195 PE and 425 PMMA signals, giving 620 backscatter traces for subsequent analysis. The selected size belongs to the 38–57 µm nominal particle-diameter range described for the original microspheres [4]. All subsequent window-sensitivity analyses were performed on this fixed PE–PMMA subset.

The original measurements were acquired using a single-element 40 MHz ultrasonic transducer with a 9 mm focal length and 90% -6 dB fractional bandwidth. Excitation was provided by a monocycle pulse generator at a pulse repetition rate of 15 kHz, while the received backscatter signals were amplified by 40 dB and digitized using a 14-bit, 10 GS/s acquisition system [4]. Although the original acquisition system operated at 10 GS/s, frequency was represented in normalized units of cycles/sample so that the analysis focused on relative spectral behavior rather than physical frequency scaling. The sample was scanned in the lateral x-y plane with a 10 µm step size, producing spatially distributed RF backscatter traces.

B. Peak-Centered Echo Extraction and Analysis-Window Selection

The location of the dominant backscatter echo varied among the selected waveforms; therefore, applying an identical absolute sample range to all signals would not consistently isolate the same echo region. For each waveform $x_i[n]$ the sample corresponding to the maximum absolute amplitude was identified as

$$p_i = \arg max|x_i[n]| \quad (1)$$

Where p_i denotes the dominant echo-peak location of the i^{th} signal. A segment of length W was subsequently extracted relative to this peak as

$$x_i^{(w)}[m] = x_i\left[p_i - \frac{W}{2} + m\right], m = 0,1,2 \dots, W-1 \quad (2)$$

Four analysis-window lengths were considered,

$$W \in \{64, 128, 256, 384\} \quad (3)$$

These window lengths permitted all 620 selected PE and PMMA traces to be retained throughout the analysis. The variation of W therefore provided a controlled means of examining whether PE–PMMA spectral-feature differences remained stable as the amount of echo content included in the analysis changed. The general influence of finite signal windows on Fourier-based spectral estimation is well established [10].

C. Spectral Feature Extraction

Each peak-centered echo segment was subjected to an identical spectral-processing procedure. The segment mean was first removed to reduce the DC offset, after which a Hamming taper was applied to reduce endpoint discontinuities and associated spectral leakage prior to Fourier analysis [10]. The use of data tapers is a standard consideration in finite-record DFT analysis because the window function influences the resulting spectral representation [10]. For a segment of length W, the processed signal was defined as;

$$y_i^w[m] = \left(x_i^{(w)}[m] - \bar{x}_i^{(w)}\right) h[m],\ m = 0,1, \dots . W-1 \quad (4)$$

Where $\bar{x}_i^{(w)}$ denotes the mean of extracted segment and h[m] is the Hamming taper;

$$h[m] = 0.54 - 0.46\cos\left(\frac{2\pi m}{W-1}\right) \quad (5)$$

The discrete Fourier transform (DFT) was subsequently evaluated using the FFT, and the non-negative-frequency squared-magnitude spectrum was obtained as;

$$P_i[k] = |Y_i[k]|^2 \quad , k = 0, 1, 2, \dots \dots, \frac{W}{2} \quad (6)$$

Frequency was represented in normalized form because no physical sampling interval was assumed for the processed signals,

$$f_k = \frac{k}{W} \text{ Cycles per sample} \quad (7)$$

Frequency-domain descriptors have previously been applied to backscattered ultrasonic signals, including spectral-centroid estimation from pulse-echo RF data [13]. In the present study, three power-weighted spectral descriptors were evaluated: spectral centroid, spectral spread, and normalized spectral entropy. The spectral centroid, was calculated as;

$$C_i = \frac{\sum_k f_k p_{i_k}}{\sum_k p_{i_k}} \quad (8)$$

The spectral spread, representing the dispersion of spectral energy about the centroid, was calculated as;

$$S_i = \sqrt{\frac{\sum_k (f_k - C_i)^2 P_i[k]}{\sum_k P_i[k]}} \quad (9)$$

For entropy calculation, the squared-magnitude spectrum was converted into a normalized spectral distribution,

$$p_i[k] = \frac{P_i[k]}{\sum_k P_i[k]} \quad (10)$$

And normalized spectral entropy was determined as;

$$H_i = -\frac{\sum_{k:p_{i[k]>0}} p_i[k] \ln p_i[k]}{\ln(N_f)} \quad (11)$$

Where N_f is the number of non-negative-frequency bins included in the entropy analyses.

The same feature-extraction procedure was applied to every selected PE and PMMA trace at each analysis window length, W=64, 128, 256, and 384 samples. This ensured that window length was the only processing parameter varied during the comparison. The resulting centroid, spread, and entropy values were subsequently summarized at the spatial-group level and used for statistical comparison between PE and PMMA.

D. Spatial Grouping and Statistical Comparison

The dataset contains several backscatter traces recorded at neighbouring spatial coordinates. To avoid treating closely located measurements as completely independent observations, the supplied coordinates were used to form connected spatial groups. Measurements were assigned to the same group when their coordinate positions were directly neighbouring, using $|\Delta x| \leq 1$ and $|\Delta y| \leq 1$. This resulted in 8 PE groups and 17 PMMA groups for the selected 50-µm size label. This grouping was used to reduce the effect of non-independent neighboring measurements by preventing closely located traces from being treated as fully independent observations.

For each analysis-window length, the centroid, spread, and entropy values of traces within the same spatial group were averaged. The resulting group-level values were then used to compare PE and PMMA using the mean, standard deviation, mean difference, and Hedges' g was used as a standardized indicator of PE–PMMA spectral separation and its change with window length [15], rather than as a measure of classification accuracy.

The same set of 620 PE and PMMA traces was retained for all four analysis-window lengths, ensuring a consistent basis for comparison. All preprocessing, spectral-feature extraction, spatial grouping, and statistical procedures were applied identically at each window length. Therefore, the observed changes in feature separation can be interpreted primarily in relation to the selected echo-analysis window rather than changes in the analyzed signal set.

E. Analysis Consistency and Window Validity

Before feature extraction, the validity of each candidate peak-centered window was checked for all selected PE and PMMA traces. Window lengths of 64, 128, 256, and 384 samples could be applied to all 620 signals without exceeding the available waveform boundaries. A 512-sample window was also initially examined; however, it could not be applied to 10 PMMA traces and was therefore excluded to maintain an identical signal set across all comparisons. The same preprocessing, spectral-feature extraction, and group-level analysis procedure was subsequently applied at every retained window length, ensuring that analysis-window length was the only processing parameter intentionally varied.

IV. Results and Discussion

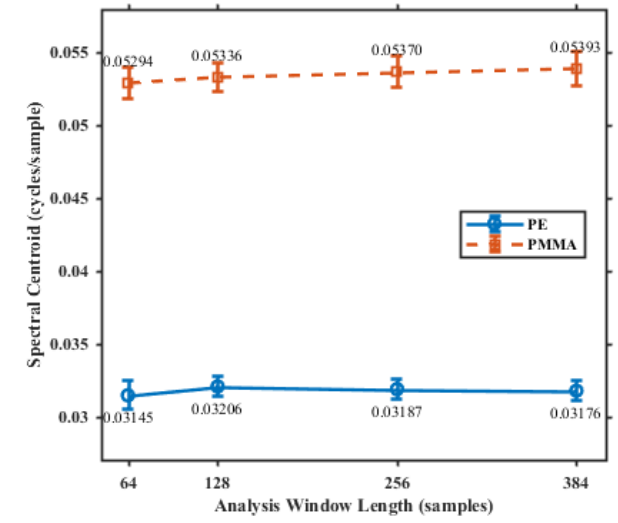
The effect of echo-analysis window length was examined using the group-level spectral features obtained from 8 PE and 17 PMMA spatial groups. Across all four window lengths, PMMA showed higher mean values than PE for spectral centroid, spectral spread, and normalized spectral entropy. However, the amount of PE–PMMA separation did not respond to window length in the same way for all three features. Fig. 2 shows the variation of the three spectral features with window length.

A. Spectral Feature Trends

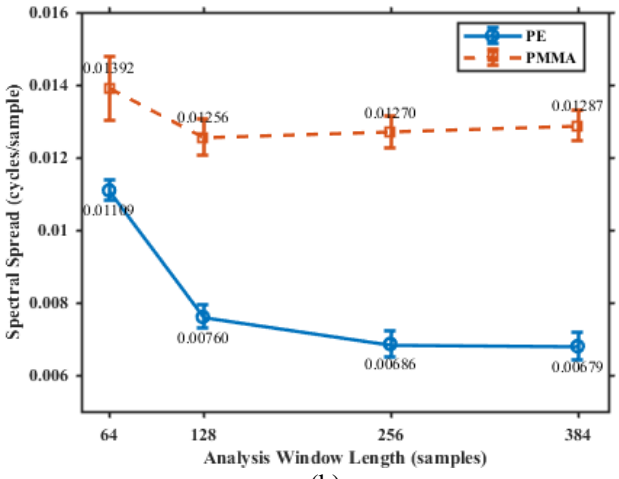
As shown in Fig. 2(a), spectral centroid was relatively stable across the four window lengths. The PE mean remained between 0.03145 and 0.03206 cycles/sample, while the PMMA mean varied only from 0.05294 to 0.05393 cycles/sample. More importantly, the PE–PMMA centroid difference remained within a narrow range of 0.02131–0.02217 cycles/sample. From W=64 to W=384, this difference increased by only about 3.2%. Therefore, changing the amount of echo data included in the analysis had only a small effect on centroid-based PE–PMMA separation

A different behavior was observed for spectral spread, as shown in Fig. 2(b). The mean PE spread decreased noticeably as the window became longer, from 0.01109 cycles/sample at W=64 to 0.00680 cycles/sample at W=384. The PMMA spread changed much less over the same range. Consequently, the PE–PMMA spread difference increased from 0.00283 to 0.00608 cycles/sample. This corresponds to an increase of approximately 115%, showing that spectral spread was strongly affected by analysis-window length.

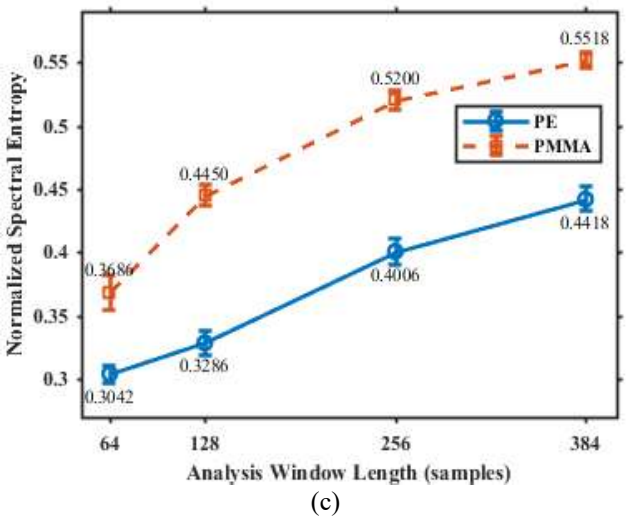
The variation in normalized spectral entropy is shown in Fig. 2(c). The PE–PMMA entropy difference was 0.06440 at W=64, increased to 0.11638 at W=128, and reached 0.11944 at W=256. It then decreased slightly to 0.11001 at W=384. Entropy therefore showed clear window sensitivity, but unlike spread, its response was non-monotonic. This suggests that entropy changes as additional spectral content from the surrounding echo waveform is included in the analysis.



(a)



(b)



(c)

Figure 2. Effect of echo-analysis window length on group-level spectral features for PE and PMMA (a) Spectral Centroid (b) Spectral Spread (c) Normalized Spectral Entropy. Error bars represent the standard deviation across connected spatial groups

B. Effect of Window Length on PE-PMMA Separation

To complement the feature trends shown in Fig. 2(a)–(c), the standardized separation between PE and PMMA was evaluated using Hedges' g. The resulting values are summarized in Table I.

TABLE I. STANDARDIZED PE–PMMA SEPARATION ACROSS ECHO-ANALYSIS WINDOW LENGTHS

Window length (samples)	Centroid	Spread	Entropy
64	20.24	3.66	5.23
128	22.68	10.84	13.21
256	21.16	13.81	14.17
384	20.21	14.67	14.28

Spectral centroid showed the most consistent standardized separation across the investigated windows. Its Hedges' g remained between 20.21 and 22.68, with no systematic increase or decrease as the window length changed. This agrees with Fig. 2(a), where the PE–PMMA centroid difference remained nearly constant across all four windows.

In contrast, spectral spread showed a clear dependence on window length. Hedges' g increased from 3.66 at W=64 to 10.84 at W=128, 13.81 at W=256, and 14.67 at W=384. This trend confirms the behavior observed in Fig. 2(b), where the separation between the PE and PMMA spread values increased as a longer portion of the echo signal was analyzed.

Normalized spectral entropy also showed a strong increase in standardized separation. Hedges' g increased from 5.23 at W=64 to 13.21 at W=128 and then remained close to 14 for W=256 and W=384. Although the absolute entropy difference in Fig. 2(c) decreased slightly at the longest window, the standardized separation remained nearly unchanged because the variation among the spatial groups was also small.

Overall, the effect-size analysis confirms that window sensitivity is feature dependent. Spectral centroid maintained comparatively stable PE–PMMA separation, whereas spread and entropy varied more strongly with window length. Hedges' g is therefore used here as a descriptive measure of standardized separation within the analyzed dataset.

C. Interpretation of Window Sensitivity

The results indicate that the effect of echo-analysis window length is feature dependent. Spectral centroid remained comparatively stable across all four windows, suggesting that the energy-weighted spectral location was only weakly influenced by the amount of echo content included in the analysis. In contrast, spectral spread changed substantially with increasing window length, while normalized spectral entropy also showed clear variation and a non-monotonic PE–PMMA difference.

This behavior is consistent with the information represented by the three descriptors. Centroid mainly reflects the spectral energy location, whereas spread and entropy

depend more strongly on how that energy is distributed across the spectrum. As longer windows include additional echo and surrounding waveform components, spread and entropy are therefore more sensitive to the selected analysis duration. This agrees with the established influence of finite signal selection on Fourier-based spectral analysis [10] and with reported signal-length effects in ultrasonic spectral-entropy analysis [14].

Overall, the findings show that feature separation should be considered together with robustness to window selection. Within the investigated PE–PMMA subset, spectral centroid showed the greatest consistency, while spread and entropy were more dependent on the selected echo-analysis window.

V. Conclusion

This study investigated the influence of echo-analysis window length on spectral-feature differences between PE and PMMA ultrasonic backscatter signals. Peak-centered windows of 64, 128, 256, and 384 samples were evaluated using spectral centroid, spectral spread, and normalized spectral entropy. The results showed that window sensitivity is feature dependent: spectral centroid remained comparatively stable across the tested windows, while spectral spread and entropy varied more strongly with the analyzed signal duration.

From a Digital Signal Processing (DSP) perspective, these findings show that feature extraction quality depends not only on the selected descriptor, but also on the consistency of the signal-segmentation procedure. A spectral feature may provide strong material separation while still being highly sensitive to window length. Therefore, analysis-window selection should be treated as an explicit DSP design parameter when developing ultrasonic characterization methods. Evaluating feature stability across multiple window lengths can improve the robustness, reproducibility, and interpretability of spectral analysis.

Within the investigated PE–PMMA subset, spectral centroid provided the most consistent response to window variation, whereas spread and entropy required greater attention to window configuration. Future work should extend this framework to additional particle sizes and materials and investigate adaptive or data-driven window-selection methods to further improve the reliability of ultrasonic DSP-based microplastic characterization.

References

[1] World Health Organization, *Microplastics in Drinking-Water*. Geneva, Switzerland: World Health Organization, 2019, ISBN: 978-92-4-151619-8.

[2] I. Abimbola, M. McAfee, L. Creedon, and S. Gharbia, "In-situ detection of microplastics in the aquatic environment: A systematic literature review," *Science of the Total Environment*, vol. 934, Art. no. 173111, 2024, doi: 10.1016/j.scitotenv.2024.173111.

[3] R. Fernandes, R. Martins, and C. Marques, "A critical review of microplastics characterisation in aquatic environments: Recent trends in the last 10 years," *Analytical Methods*, vol. 17, no. 7, pp. 1415–1427, 2025, doi: 10.1039/D4AY01802H.

[4] N. Zarrabi, E. M. Strohm, H. Rezvani, M. Lisondra, N. Yousefi, S. Saeedi, and M. C. Kolios, "High-frequency ultrasound combined with deep learning enables identification and size estimation of microplastics," *npj Emerging Contaminants*, vol. 2, Art. no. 9, 2026, doi: 10.1038/s44454-026-00029-1.

[5] J.-L. Xu, K. V. Thomas, Z. Luo, and A. A. Gowen, "FTIR and Raman imaging for microplastics analysis: State of the art, challenges and prospects," *TrAC Trends Anal. Chem.*, vol. 119, Art. no. 115629, Oct. 2019, doi: 10.1016/j.trac.2019.115629.

[6] K. Han, M. Huang, Z. Wang, C. Shi, Z. Wang, J. Guo, W. Liu, L. Lei, and Q. Guo, "Innovative methods for microplastic characterization and detection: Deep learning supported by photoacoustic imaging and automated pre-processing data," *J. Environ. Manage.*, vol. 359, Art. no. 120954, May 2024, doi: 10.1016/j.jenvman.2024.120954.

[7] M. Huang, K. Han, W. Liu, Z. Wang, X. Liu, and Q. Guo, "Advancing microplastic surveillance through photoacoustic imaging and deep learning techniques," *J. Hazard. Mater.*, vol. 470, Art. no. 134188, May 2024, doi: 10.1016/j.jhazmat.2024.134188.

[8] Y. van den Brink, N. Dam, Y. Wang, and Y. Tang, "Development and operational characterization of an acoustofluidic trap for microplastic separation from water systems," *Sep. Purif. Technol.*, vol. 395, pt. 3, Art. no. 137713, Jul. 2026, doi: 10.1016/j.seppur.2026.137713.

[9] R. Smolíková, M. P. Wachowiak, and J. M. Zurada, "An information-theoretic approach to estimating ultrasound backscatter characteristics," *Comput. Biol. Med.*, vol. 34, no. 4, pp. 355–370, Jun. 2004, doi: 10.1016/S0010-4825(03)00072-6.

[10] F. J. Harris, "On the use of windows for harmonic analysis with the discrete Fourier transform," *Proc. IEEE*, vol. 66, no. 1, pp. 51–83, Jan. 1978, doi: 10.1109/PROC.1978.10837.

[11] B. Wu and Y. Huang, "Flaw detection in highly scattering materials using a simple ultrasonic sensor employing adaptive template matching," *Sensors*, vol. 22, no. 1, Art. no. 268, 2022, doi: 10.3390/s22010268.

[12] N. Zarrabi, E. M. Strohm, H. Rezvani, M. Lisondra, N. Yousefi, S. Saeedi, and M. C. Kolios, "Dataset for high-frequency ultrasound-based microplastic identification and size estimation," *Zenodo*, 2026, doi: 10.5281/zenodo.18484378.

[13] H. Kim and S. W. Heo, "Time-domain calculation of spectral centroid from backscattered ultrasound signals," *IEEE Trans. Ultrason., Ferroelectr., Freq. Control*, vol. 59, no. 6, pp. 1193–1200, Jun. 2012, doi: 10.1109/TUFFC.2012.2309.

[14] F. Xu, Y. Xu, C. Liu, and D. Ta, "The spectrum entropy estimation method for ultrasonic backscattering signal in cancellous bone," *Acta Acustica*, vol. 41, no. 3, pp. 281–286, 2016, doi: 10.15949/j.cnki.0371-0025.2016.03.002.

[15] L. V. Hedges, "Distribution theory for Glass's estimator of effect size and related estimators," *J. Educ. Stat.*, vol. 6, no. 2, pp. 107–128, Summer 1981, doi: 10.3102/10769986006002107