
# Automatic Detection of White Shrimp Feeding Activity Using Acoustic Signals

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**Abstract.**

*Feeding management is one of the main challenges in white shrimp (Penaeus vannamei) farming, as feed can represent approximately 40% to 60% of operational costs. Inadequate feeding strategies increase production costs and may also compromise water quality, contributing to environmental impacts. Since shrimp feeding activity produces impulsive acoustic events commonly described as clicks, passive acoustic monitoring represents a promising approach for supporting more precise feeding decisions. This study analyzes acoustic recordings collected over an 8-hour period at a sampling rate of 192 kHz. The experiments were conducted with shrimp maintained in tanks and fed at hourly intervals. An automatic feeding activity detection algorithm was developed using classical digital signal processing techniques, with acoustic onset detection functions computed in the 8–20 kHz frequency band. Detected clicks were counted within one-minute windows to characterize temporal variations in feeding activity. The results showed clear hourly peaks in click occurrence, consistent with the feed supply schedule. These findings demonstrate the feasibility of using acoustic signals to monitor shrimp feeding activity. Although shrimp clicks are impulsive events with spectral content extending beyond the human audible range, the 8–20 kHz band was sufficient to capture feeding-related activity, supporting the potential use of conventional audio acquisition systems. Because the proposed algorithm is based on low-complexity signal processing methods, it is suitable for implementation on devices with limited computational resources. This opens opportunities for embedded acoustic monitoring systems in laboratory and commercial aquaculture environments, contributing to more precise, efficient, and sustainable shrimp farming.*

**Keywords.**

*Automatic detection; Precision aquaculture; Shrimp feeding; Passive acoustic monitoring; Acoustic signal processing.*

# 1 Introduction

Brazil has become one of the leading shrimp-farming producers in the Americas, with production strongly concentrated in the Northeast region (Valenti et al., 2021). This activity is mainly based on the cultivation of the white shrimp (*Penaeus vannamei*). Despite its economic relevance, feeding management remains one of the main challenges in shrimp farming, as feed accounts for approximately 40% to 60% of total production costs (Napaumpaiporn et al., 2013; Zhou et al., 2017). Inaccurate feed management not only increases production costs but also compromises water quality (Tsai et al., 2022). Underfeeding limits shrimp growth, whereas overfeeding leads to feed waste and increases the organic load in ponds, affecting animal health and increasing costs associated with aeration and farm management (Peixoto et al., 2020; Reis et al., 2022; Sánchez-Gendriz et al., 2025).

It is known that the feeding process of white shrimp produces acoustic waves (Peixoto and Soares, 2025). Therefore, acoustic detection can be used as an indicator of feeding activity (Peixoto et al., 2020; Sánchez-Gendriz et al., 2025). In addition, the efficiency of feeding systems based on acoustic detection has been supported by comparisons of shrimp productivity indices among three feeding strategies: manual feeding, timer-controlled feeding, and acoustically controlled feeding. These studies reported the highest productivity when using sound-based feeding control. Moreover, under this system, water-quality-related parameters were not negatively affected (Napaumpaiporn et al., 2013).

In this context, passive acoustic monitoring offers a promising approach for supporting more precise and data-driven feeding management in shrimp farming. Acoustic methods can provide non-invasive and continuous information on feeding-related activity, creating opportunities for the development of embedded monitoring systems suitable for precision aquaculture applications.

### 1.1 Objective

The objective of this study is to develop a lightweight and computationally efficient acoustic detector capable of inferring shrimp feeding activity from streaming acoustic data.

*Specific Objectives*

The specific objectives are:

1. To develop a lightweight and computationally efficient method for the automatic detection of shrimp feeding clicks, suitable for implementation in low-resource devices and real-time monitoring systems.
2. To apply and validate the proposed method using passive acoustic monitoring data collected during real shrimp feeding events, demonstrating its potential for monitoring feeding activity.
3. To analyze the temporal patterns of detected clicks and discuss how this information can support shrimp feeding management in controlled environments and commercial farming systems.

# 2 Methodology

### 2.1 Acoustic Dataset

The acoustic dataset used in this study was collected under controlled laboratory conditions with white shrimp, *Penaeus vannamei*, as part of the study described in (Peixoto et al., 2025). The experiment was conducted in rectangular polyethylene tanks measuring 48 × 24 × 24 cm, with a stocking density of 42 shrimp/m², corresponding to six animals per tank.

The acoustic recording system consisted of an omnidirectional AS-1 hydrophone (Aquarian Audio, USA), with a linear frequency response from 1 Hz to 100 kHz and a sensitivity of −208 dB re 1 V/μPa. The hydrophone was coupled to a PA4 preamplifier (Aquarian Audio, USA) with a gain of 26 dB. It was positioned at the center of each tank, 15 cm above the bottom, and connected to an F6 digital recorder (Zoom Inc., USA). The recordings were digitized at a sampling rate of 192 kHz with 16-bit resolution, allowing acoustic signals with frequencies up to 96 kHz to be captured.

The dataset comprised four independent acoustic recordings. Each recording lasted eight hours and followed the same monitoring schedule, starting at 08:00 and ending at 16:00. The beginning of each recording coincided with the first feeding event of the day in all treatments, while the end of the recording occurred one hour after the last scheduled feeding event. During the monitoring period, shrimp were fed at hourly intervals. This experimental design provided repeated acoustic records with known feeding times, simulating a periodic feeding regime similar to timer-based feeding strategies used in productive farms. Therefore, the dataset allowed the temporal response of the proposed detector to be evaluated under controlled conditions that are relevant to automated feeding management in precision aquaculture.

### 2.2 Acoustic Click Detection Approach

The proposed method is based on the detection of impulsive acoustic events produced during shrimp feeding activity. These events, commonly described as clicks, are characterized by short duration and abrupt spectral variations. For this reason, the detection strategy was formulated using onset detection functions (ODFs), which are commonly used to identify sudden changes in acoustic signals (Bello et al., 2005; Dixon, 2006; Mounir et al., 2021).

In this study, two spectral ODFs were adopted: a modified High-Frequency Content function and a modified Spectral Flux function. These descriptors were selected because they are computationally simple, interpretable, and suitable for real-time or near-real-time implementation in low-resource devices. Both functions were computed from the magnitude spectrum obtained using the Short-Time Fourier Transform (STFT), a standard representation for analyzing the time-varying spectral content of acoustic signals (Sanchez-Gendriz, 2021). The analysis was restricted to the 8–20 kHz frequency band, which is compatible with conventional audio acquisition systems. This band selection also evaluates the feasibility of detecting shrimp feeding clicks using a reduced spectral range, supporting future optimization of recording systems for precision aquaculture applications.

Figure 1 summarizes the complete processing workflow of the proposed acoustic click detection method. The procedure begins with the input acoustic signal, which is transformed into a time-frequency representation using short-time spectral analysis. From this representation, the magnitude spectrum is restricted to the selected frequency band, providing the spectral information used by the subsequent detection stages.

Two complementary ODFs are then computed from the selected spectral magnitudes. The modified High-Frequency Content descriptor, $(dHFC(n))$, summarizes the temporal increase of the total band-limited magnitude, providing a global measure of abrupt acoustic energy variation. The modified Spectral Flux descriptor, $(SF(n))$, evaluates positive frame-to-frame changes at each frequency bin before aggregation, preserving more localized spectral variations. Although both descriptors are based on positive spectral changes, they emphasize different aspects of the same impulsive acoustic phenomenon.

The two descriptors are combined into a composite onset detection function, ($Z(n)$), which reinforces frames in which both measures indicate an abrupt acoustic change. Candidate click events are identified by applying a threshold-based decision rule to $Z(n)$. The detected events are then aggregated into one-minute windows, producing an event-count time series that represents the temporal evolution of feeding-related acoustic activity. This final output allows the detected acoustic events to be compared with scheduled feeding times and provides a practical indicator for precision aquaculture monitoring.

The following subsections describe each processing stage in detail, including the modified HFC descriptor, the modified Spectral Flux descriptor, the composite ODF, and the threshold-based temporal aggregation procedure.

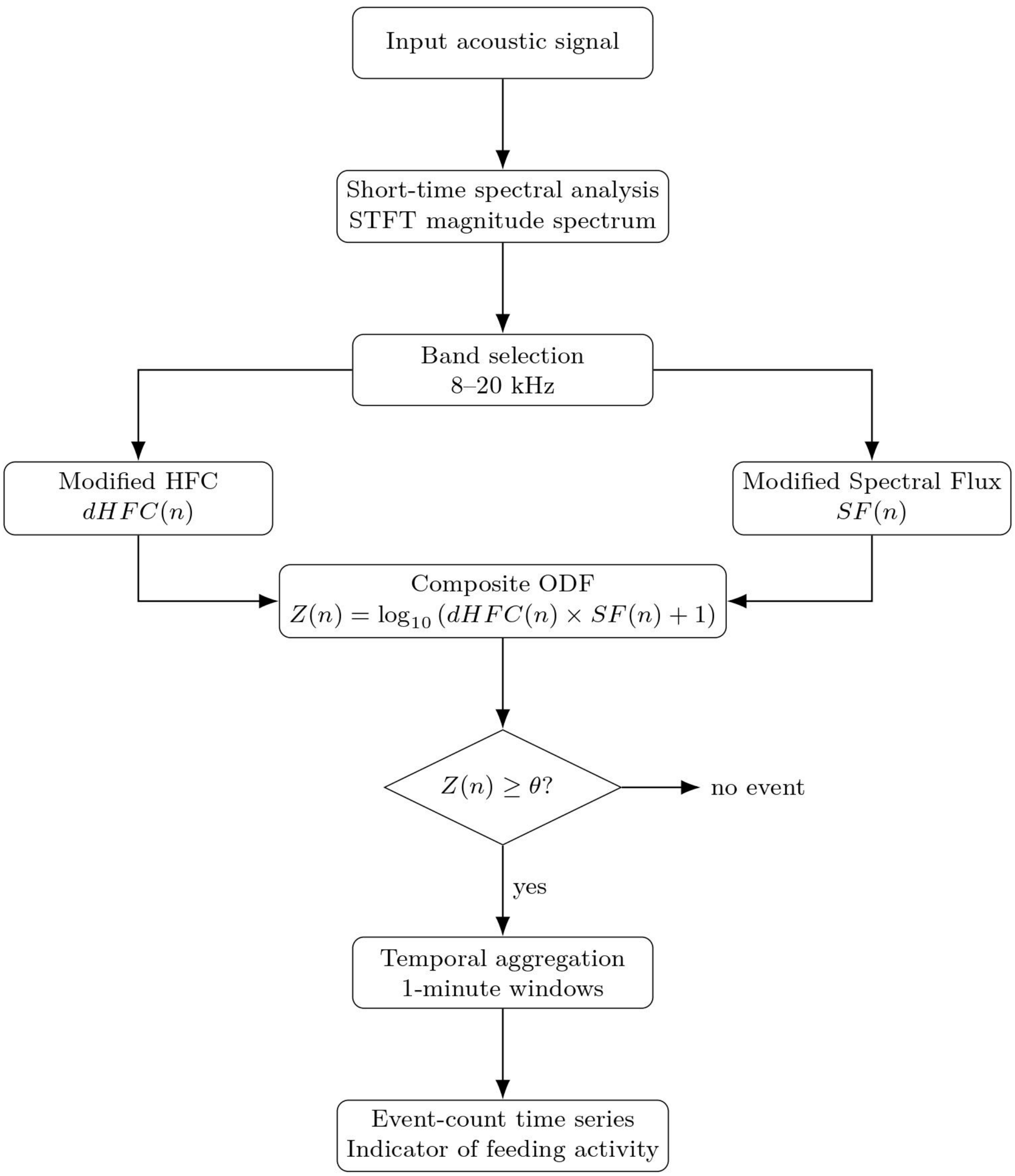

**Figure 1. Algorithmic workflow of the proposed acoustic click detection method. The input acoustic signal is converted into a time-frequency representation using short-time spectral analysis. After band selection, two complementary onset detection functions are computed: the modified High-Frequency Content descriptor, (dHFC(n)), and the modified Spectral Flux descriptor, (SF(n)). These descriptors are combined into the composite onset detection function, (Z(n)), which is thresholded to identify candidate click events. The detections are aggregated into one-minute windows to obtain an event-count time series used as an indicator of shrimp feeding activity.**

### *2.2.1 Modified High-Frequency Content Function*

The High-Frequency Content (HFC) function is commonly used for onset detection because transient acoustic events tend to produce abrupt increases in spectral energy (Bello et al., 2005; Dixon, 2006). In this study, a modified HFC-based descriptor was used to emphasize sudden increases in acoustic energy associated with shrimp feeding clicks.

For each STFT analysis frame, the spectral magnitudes within the selected frequency band were summed, producing a frame-level measure of band-limited acoustic energy. The temporal difference between consecutive frames was then computed. Since feeding clicks are expected to appear as abrupt energy increases, only positive variations were retained using half-wave rectification. Finally, logarithmic compression was applied to reduce the dynamic range of the detection function.

Thus, the modified HFC descriptor can be interpreted as the logarithmically compressed positive temporal variation of the band-limited spectral magnitude. This formulation highlights abrupt increases in acoustic energy potentially associated with feeding clicks, while preserving a simple structure suitable for implementation in low-resource devices.

### *2.2.2 Modified Spectral Flux Function*

Spectral Flux measures spectral changes between consecutive frames and is widely used for acoustic onset detection (Bello et al., 2005; Dixon, 2006). In this study, a modified Spectral Flux descriptor was used to emphasize abrupt positive changes in spectral magnitude associated with shrimp feeding clicks.

For each frequency bin, the magnitude difference between consecutive frames was computed. Only positive differences were retained through half-wave rectification, since the objective was to emphasize sudden spectral increases rather than decreases. These positive increments were then summed across the selected frequency band (8-20 kHz), producing a single detection value for each frame. Finally, logarithmic compression was applied to reduce the influence of large amplitude variations and stabilize the dynamic range of the descriptor.

Although the modified Spectral Flux and the modified HFC descriptor are both based on positive frame-to-frame variations in spectral magnitude, they are not mathematically equivalent. The modified HFC first sums the spectral magnitudes across the band and then evaluates the positive temporal variation of this band-limited magnitude. In contrast, the modified Spectral Flux first retains positive frame-to-frame variations at each frequency bin and only then sums these increments across the band. Therefore, the modified HFC provides a more global measure of energy increase, whereas the modified Spectral Flux preserves local positive spectral changes before aggregation. These related but complementary properties support their combined use for detecting feeding-related impulsive events.

### *2.2.3 Composite Onset Detection Function*

To improve the robustness of click detection, the two modified ODFs were combined into a composite onset detection function. The rationale behind this combination is that a shrimp feeding click should produce both an abrupt increase in band-limited acoustic energy and rapid positive changes across the spectral distribution. Therefore, combining the modified HFC and modified Spectral Flux descriptors reinforces events that are simultaneously emphasized by both functions.

The composite ODF was computed as illustrated in equation 1:

$$Z(n) = log10(dHFC(n) \times SF(n) + 1) \quad (1)$$

where $Z(n)$ is the composite onset detection function at frame $n$, $dHFC(n)$ is the modified HFC descriptor, and $SF(n)$ is the modified Spectral Flux descriptor. The addition of 1 avoids numerical issues when the product is close to zero, while the logarithmic transformation compresses the dynamic range of the composite response.

This formulation favors frames in which both descriptors indicate an abrupt acoustic change. As a result, isolated fluctuations that appear strongly in only one descriptor have less influence on the final detection function. This provides a lightweight and interpretable strategy for detecting shrimp feeding clicks from acoustic recordings, while remaining suitable for future implementation in real-time and low-resource monitoring systems

*2.2.4 Threshold-Based Detection and Temporal Aggregation*

Candidate feeding clicks were identified by applying a fixed threshold to the composite ODF, ($Z(n)$). Frames with $Z(n) \geq 0.01$ were classified as acoustic events. This threshold was empirically defined from the observed distribution of $Z(n)$ during periods with feeding-related acoustic activity.

The detected events were aggregated into one-minute windows to obtain an estimate of feeding activity. For each window, the number of detected clicks was counted, generating a click-rate profile over the 8-hour recording period. This temporal resolution was chosen to support comparison with the hourly feeding schedule used in the experiment.

The resulting click-count series was used to evaluate whether increases in acoustic activity occurred near known feeding times. Peaks in the number of detected events were interpreted as feeding-related responses when they were temporally consistent with feed supply. In this way, the detector output was converted from frame-level acoustic events into an operational indicator of feeding activity, supporting its potential use in precision aquaculture and automated feeding management systems.

# 3 Results and Discussions

## 3.1 Time-frequency Characteristics of Acoustic Recordings

The automatic detection of shrimp feeding clicks is challenging because these events are short, impulsive, and often partially masked by background noise. In aquaculture systems, continuous or intermittent sound sources, such as water recirculation systems, aerators, pumps, and valve operations, may overlap with the acoustic signature of feeding activity (Peixoto and Soares, 2025). As a result, detection strategies based only on amplitude variations in the time domain may be unreliable, especially when the background acoustic energy is high.

Figure 1 shows a representative 15-second segment of the acoustic data collected during the experiment. The upper panel presents the time-domain waveform, while the lower panel shows the corresponding spectrogram. In the waveform, individual click events are not clearly distinguishable because the signal amplitude is dominated by background noise and other acoustic components. This illustrates the difficulty of detecting feeding-related clicks directly from time-domain amplitude information.

The spectrogram provides additional information about the acoustic structure of the signal. A persistent sound component is observed below 10 kHz, with stronger energy concentrated below approximately 5 kHz. This component is likely associated with the water recirculation system used to maintain water quality in the experimental tanks. Short vertical structures can also be observed in the time-frequency representation, indicating the occurrence of impulsive acoustic events.

These structures are consistent with click-like sounds produced during shrimp feeding activity. However, their contrast relative to the background remains limited, showing that reliable detection requires descriptors specifically designed to emphasize abrupt spectral changes.

These characteristics motivated the use of onset detection functions computed from the time-frequency representation of the signal. The proposed composite ODF was designed to enhance short impulsive events associated with feeding activity while reducing the influence of persistent background components. This is relevant for precision aquaculture applications, in which acoustic monitoring systems must operate under realistic noise conditions and provide robust indicators of feeding activity for automated or decision-support feeding strategies.

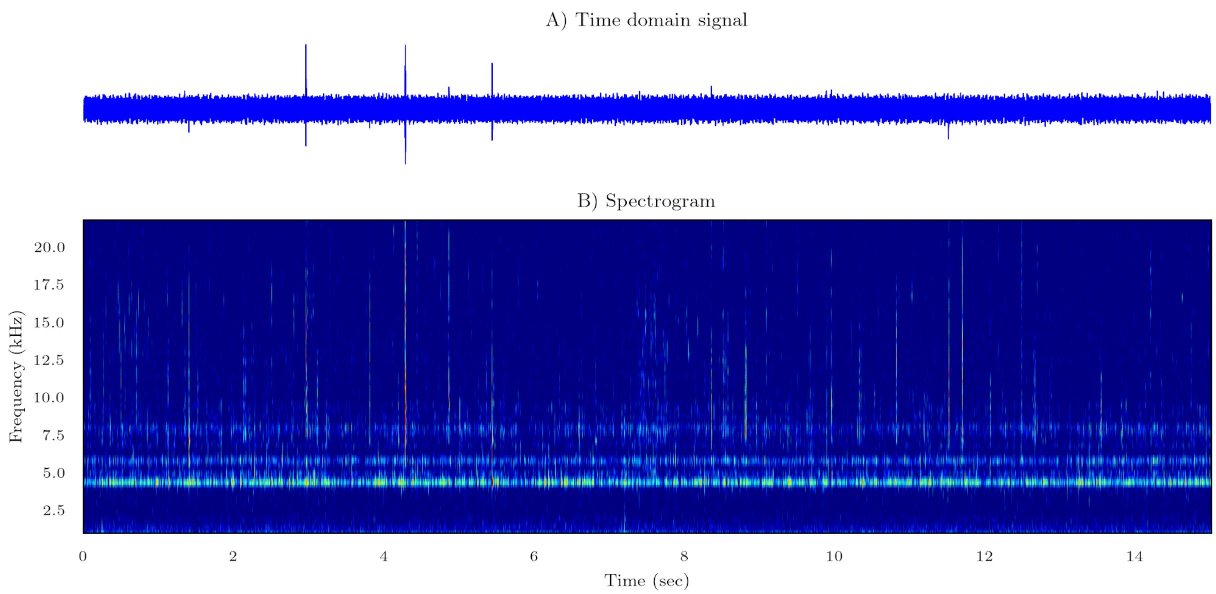


**Figure 1. Representative 15-second acoustic segment recorded during the shrimp feeding experiment. The upper panel shows the time-domain waveform, and the lower panel shows the corresponding spectrogram. The signal contains persistent background components, mainly concentrated near to 5 kHz, and short impulsive events visible as vertical spectral structures.**

### 3.2 Composite ODF Response for Click Detection

The composite onset detection function (ODF) described in the methodology was developed to enhance short impulsive events associated with shrimp feeding activity under noisy acoustic conditions. Figure 2 shows the response of the proposed detection procedure for the same 15-second segment presented in Figure 1. The first two panels show the modified HFC and modified Spectral Flux descriptors, respectively. The third panel shows the composite ODF, $Z(n)$, and the fourth panel presents the resulting binary event detection.

For this illustrative example, a fixed threshold of 0.01 was applied to $Z(n)$. The modified HFC and modified Spectral Flux descriptors show related temporal patterns, with several peaks occurring at similar instants. However, both descriptors also present residual background fluctuations, which may reduce the contrast between click events and non-event regions. This behavior is expected because each descriptor responds to abrupt spectral changes in a different but related manner.

The composite ODF improves the separation between impulsive events and background activity. By multiplying the modified HFC and Spectral Flux descriptors, the method emphasizes frames in which both descriptors simultaneously indicate an abrupt acoustic change. As a result, low-level background fluctuations are attenuated, and the baseline activity becomes less prominent.

This effect can be observed in the third panel of Figure 2, where only a reduced number of peaks remain clearly highlighted.

The final detection output is obtained by applying the predefined threshold to the composite ODF. In the example shown, only the most prominent peaks in $Z(n)$ triggered detections, indicating the occurrence of candidate click events. This result illustrates how the composite ODF converts the acoustic information into a sparse sequence of detected events, which can then be aggregated over time to estimate feeding activity. This frame-level detection step is essential for generating temporal indicators suitable for precision aquaculture applications, such as monitoring feeding responses under timer-based or automated feeding regimes.

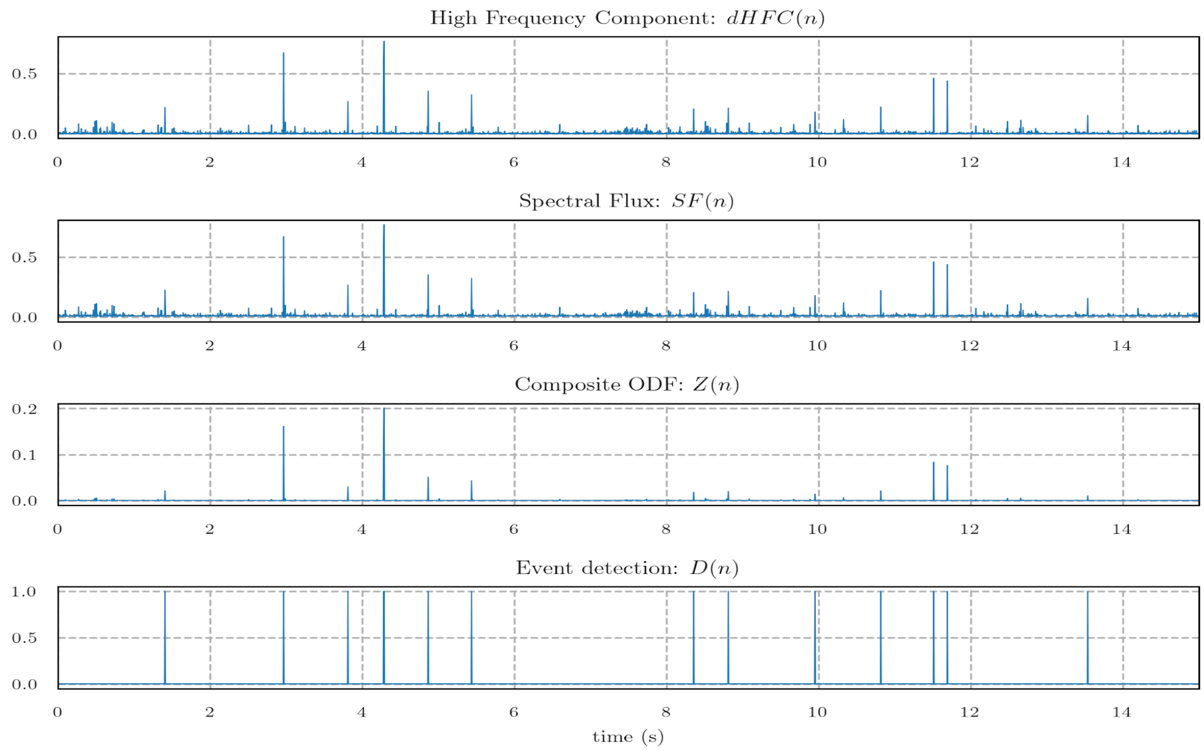


**Figure 2. Response of the proposed click detection procedure for a representative 15-second acoustic segment. The first panel shows the modified High-Frequency Content descriptor, the second panel shows the modified Spectral Flux descriptor, and the third panel shows the composite onset detection function, (Z(n)). The fourth panel presents the binary event detection obtained by applying a fixed threshold of 0.01 to (Z(n)). The composite ODF attenuates background fluctuations and emphasizes peaks simultaneously highlighted by both descriptors, resulting in a sparse sequence of candidate shrimp feeding clicks.**

### 3.3 Temporal Aggregation of Detected Clicks Across Feeding Cycles

The detected click events were aggregated into one-minute windows to evaluate the temporal dynamics of shrimp feeding activity across the complete monitoring period. Figure 3 shows the aggregated detections for the four independent 8-hour recordings. In all recordings, recurrent peaks in the event-count series can be observed near the hourly feeding times, indicating that the proposed detector captured acoustic responses temporally associated with feed supply.

The results show a clear periodic structure in the detected acoustic activity. Recording 1 and Recording 3 present well-defined peaks at approximately hourly intervals, with relatively low activity between feeding events. Recording 2 also shows repeated peaks near the expected feeding times, although with a higher baseline level and more pronounced fluctuations throughout the recording. Recording 4 presents stronger activity at the beginning of the monitoring period, followed by a progressive reduction in the number of detected events, while still preserving peaks near several scheduled feeding times.

These differences among recordings may reflect variability in feeding behavior across tanks, differences in shrimp activity, or changes in the acoustic background of each experimental unit. Factors such as tank-specific noise, water movement, animal distribution, and local interaction with feed pellets may influence the amplitude and temporal profile of the detected click activity. Therefore, although the hourly feeding pattern is evident, the detailed shape and intensity of the response vary among repetitions.

Overall, the one-minute aggregation of detected clicks provides a quantitative temporal indicator of feeding-related acoustic activity. By converting frame-level detections into an interpretable event-count time series, the proposed method allows acoustic responses to be evaluated in relation to scheduled feeding events. This capability is particularly relevant for precision aquaculture, as it may support long-term monitoring in productive farms and provide objective information for assessing feeding responses. In future applications, this approach could contribute to the development of automated or closed-loop feeding systems, in which feed supply is adjusted according to acoustic indicators of animal activity. Under laboratory conditions, the method may also be useful for controlled studies of feeding behavior and feed intake dynamics.

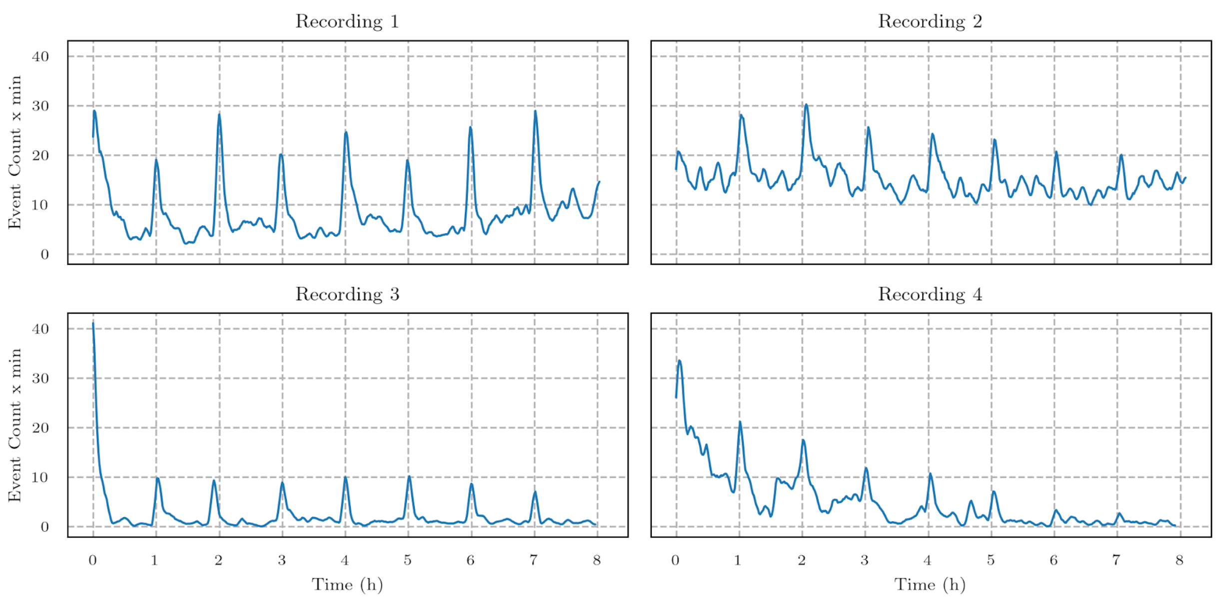


**Figure 3. Temporal aggregation of detected shrimp feeding clicks across four independent 8-hour recordings. Detected events were counted in one-minute windows, producing an event-count time series for each recording. Recurrent peaks are observed near the hourly feeding schedule, indicating that the proposed acoustic detector captured feeding-related activity patterns. Differences in baseline activity and peak intensity among recordings may be associated with tank-specific acoustic conditions and variability in shrimp feeding behavior.**

### 3.4 Computational Considerations and Implications for Precision Aquaculture

The proposed method was designed to be computationally simple and suitable for future implementation in real-time or near-real-time monitoring systems. The algorithm relies on classical digital signal processing operations, including short-time spectral analysis, band selection, frame-to-frame spectral differences, half-wave rectification, logarithmic compression, thresholding, and temporal aggregation. These operations are relatively lightweight compared with machine learning or deep learning models and do not require a large annotated training dataset.

This characteristic is particularly relevant for precision aquaculture applications, where monitoring systems may need to operate continuously under field conditions using low-cost or embedded hardware. By restricting the analysis to the 8–20 kHz band and using two interpretable spectral descriptors, the proposed approach provides a practical basis for acoustic monitoring systems that are compatible with conventional audio acquisition devices.

The one-minute aggregation of detected clicks also supports the transformation of frame-level acoustic events into an operational indicator of feeding activity. This type of temporal information may be useful for evaluating feeding responses under timer-based regimes, supporting long-term monitoring in productive farms, and guiding the future development of automated or closed-loop feeding systems. In controlled laboratory conditions, the method may also contribute to studies of feeding behavior, feed intake dynamics, and pellet palatability. These applications are relevant not only for research purposes, but also for commercial testing and optimization of feed formulations under standardized experimental conditions.

Although the results indicate the feasibility of the proposed approach, further validation is necessary before operational deployment. Future work should include systematic comparison with manually annotated reference detections, as well as a methodological procedure for setting detection parameters, such as the detection threshold, frequency band and aggregation scale. Additional studies should also evaluate embedded hardware implementation and compare the proposed method with more complex models, including deep learning-based detectors. Such comparisons are important to determine whether a simple and interpretable signal-processing approach can provide competitive performance while remaining suitable for practical use in precision aquaculture.

## Conclusion

This study presented a lightweight acoustic method for the automatic detection of feeding activity in white shrimp. The proposed approach combined modified High-Frequency Content and Spectral Flux descriptors into a composite onset detection function designed to emphasize impulsive click events associated with feeding activity.

The results showed recurrent peaks in detected acoustic activity near the scheduled feeding times across four independent 8-hour recordings. When aggregated into one-minute windows, the detections produced an interpretable event-count time series that can be used as a quantitative indicator of feeding-related activity.

These findings support the feasibility of using acoustic signals and low-complexity signal processing methods for monitoring shrimp feeding activity. The proposed method has potential for precision aquaculture applications, including long-term feeding monitoring, evaluation of feeding responses, and future integration into automated feeding management systems.

### Acknowledgments

Put any acknowledgments, such as thanks to contributing individuals or organizations, here.

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