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METHOD FOR RAILWAY NOISE EVENT DETECTION: EXPERIMENT USING MEDUSA SENSORS

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ABSTRACT

The noise generated by railway traffic is a significant source of annoyance. Energy indicators commonly used to measure sound levels are mean-based indicators that do not reflect event-based railway noise. New epidemiology studies are looking at the correlation between each train pass-by and the instantaneous annoyance of the population. In this study, we present a method for detecting railway noise events using two Medusa sensors, advanced acoustic array measurement devices capable of determining sound directionality and levels. The method combines signal processing techniques, such as Butterworth filtering, with sound localization data to identify and classify railway noise events. It was implemented as part of the GENIFER study, conducted in the commune of Savigny-sur-Orge, a complex urban environment with multiple noise sources. The results demonstrate the effectiveness of the proposed detection method in accurately identifying railway noise events, achieving high recall and precision. This methodology provides a robust framework for assessing railway noise impacts at the individual event level, paving the way for improved noise monitoring systems and a better understanding of the link between railway noise and human annoyance.

Keywords: *Railway, noise event, detection, medusa sensor*

1. INTRODUCTION

Railway noise has been shown to adversely affect the health of nearby residents, particularly by causing long-term annoyance and sleep disturbance [1]. These effects are often linked to long-term, energy-based average indicators like LAeq or LDEN. However, these indicators do not adequately capture the event-based nature of railway noise, which can be more relevant for understanding its impact.

In 2022, following the work of the French Noise Council on railway noise peaks, the French Ministry of Ecological Transition published an experimental draft decree [2], proposing to study the technical and functional relevance, as well as their readability for the public, of new event-based indicators alongside energy-based ones already used in noise regulation. This shift highlights the need for accurate event-based noise detection.

The GENIFER feasibility study (Improving Knowledge of Acoustic Factors of Instantaneous Annoyance Due to Railway Noise) [3] was conducted by Bruitparif, Gustave Eiffel University, and SNCF Réseau (France's national railway infrastructure manager). A key part of the study was the ability to detect train pass-by comprehensively to correlate event-based acoustic indicators with instantaneous annoyance rated by the survey participants. A specific detection method was developed using sound level thresholds combined with sound localization capabilities provided by Medusa [4] sensors.

Traditional noise event detection, using basic acoustic sensors without audio data, relies on exceedance algorithms [5]. These algorithms detect noise events when A-weighted sound levels surpass a given threshold for a specific duration and with a defined emergence [5,6]. However, in complex urban environments, distinguishing noise sources (e.g., road traffic, rail traffic, or air traffic) is particularly challenging.

Recent studies have shown promise in using neural networks [7] and machine learning for noise event source recognition [8], but these approaches typically require extensive audio datasets, which are difficult to collect in long-term monitoring due to privacy regulations (such as GDPR in EU countries). Moreover, these methods often fail to capture supplementary information, such as the track used or the train's direction. High-cost array set-ups have also been used to detect railways noise events and have been used for source separations methods [11].

To the best of our knowledge, no prior studies have used low-cost acoustic array measurement sensors in real-world settings to detect railway noise events. Acoustic arrays have been employed in aircraft noise monitoring [9], allowing event filtering

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based on sound direction after detection by noise level. In this study, we applied a similar methodology to improve noise threshold detection in a complex urban setting and to gather additional data, such as the train's track.
This study's objective is to develop and validate a method for detecting railway noise events using Medusa sensors in a complex urban environment.

2. METHODS

2.1 Study Area and setup

The study took place in Savigny-Sur-Orge, France, an urban area with various noise sources, including both rail and road traffic. This site was selected based on specific rail traffic criteria, with daily train counts ranging between 200 and 400. To accurately detect railway noise events, Bruitparif deployed two Medusa sensors with two cameras across each side of the railway tracks (Figure 1). In this study area, the railway contains 5 different tracks (V2B, V2, V1, EV1, V1B). The goal was to detect trains passing through tracks EV1 and V1B with the medusa 1 and the camera 1, and the ones going through V2B, V2, and V1 with medusa 2 and the camera 2.

2.2 Sensors

Medusa sensors [4], developed by Bruitparif, are acoustic array measurement devices capable of determining the dominant sound in the environment every 0.1 second by goniometric method. These sensors provide both sound level data and sound directionality information, making them particularly suited for noise source localization in complex soundscapes. The sensors operate by capturing sound across an array of 4 microphones, allowing for precise detection of noise events based on the direction of the sound source. Each sensor was calibrated prior to deployment to ensure accurate data.
Furthermore, two cameras were deployed with the medusas, the cameras were AI 360° Panoramic Fisheye Network Camera MS-C9674. It automatically detects when an object is moving and saves the video. It allowed us to have a complementary dataset of each train's pass-by videos.

Figure 1: Location and Setup of Medusas Sensors for Railway Noise Detection

2.3 Detection Algorithm – Thresholds Method

The detection method used in this study was based on a combination of sound level thresholds and sound localization data provided by the Medusa sensors.

The first step was to identify acoustic noise events when A-weighted sound levels exceed a predefined threshold for a minimum duration and with a defined emergence.

Two different thresholds methods have been used in this study. The first one utilizes a Butterworth filter (Figure 2) to process the LAeq100ms data through two distinct low-pass filters, one with a higher order (n=5) and a cut-off frequency of Wn=0.02, and the other with a lower order (n=1) and a cut-off frequency of Wn=0.002. The points where these two filtered signals intersect are used to estimate the start and end of an acoustic event. The second method is a more commonly used methodology which consists of intersecting LA50 (median level during the last 10 minutes) and the LA50 + 5 dB(A) curves.

In the absence of a standardized method for accurately determining the timestamps of noise events in railway noise monitoring systems, these intersections provide a reasonable approximation of the full event duration, capturing both the approach and departure phases of the train. This approach offers a more realistic estimation of event duration compared to other methods, such as measuring train pass-by time (LAeq,tp) or using the time span when the sound level remains within 10 dB of LAmax, as is sometimes practiced. To classify these events as railway-related, thresholds based on duration, emergence, and a minimum LAeq level were then applied.

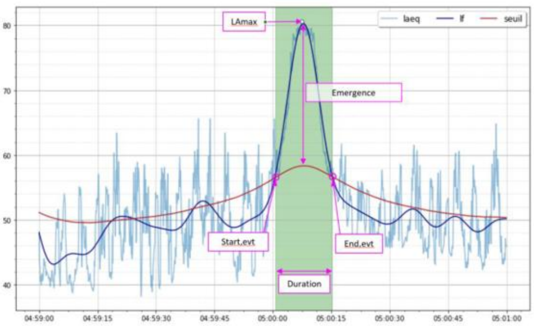

Figure 2: Low pass filter – Butterworth method

To choose the different thresholds a mix of experience-based knowledge from the Bruitparif railway noise monitoring network and the SNCF-RESEAU (France's national railway infrastructure manager) train daily traffic data and threshold used in research paper has been used. The traffic database has shown that the number of trains per day is around 350 trains per day and they can be categorized into five different groups: urban passenger trains (RER), old generation regional trains (CORAIL), new generation regional trains (TER_NG2N), new generation regional short trains (TER_AUTORAIL) and freight trains (FRET). Using the national train signature database [10] and theorical train speed, we can estimate what will be the lowest duration and LAeq received by our sensor to avoid missing too many trains. The thresholds used can be found in Table 1 and Table 2.

TABLE 1. Threshold used to detect noise events for the Butterworth method

Parameter	Description	Threshold	Unit
L_{min}	The minimum LAeq,event value	55	dB(A)
E	Difference between LAmax and minimum event value	10	dB(A)
T_{min}	Minimal event duration	5	s
T_{max}	Maximal event duration	120	s
L_{thres}	Level above threshold	60	dB(A)
T_{thres}	Time above level threshold	3	s

TABLE 2. Threshold used to detect noise events for the LA50 + 5 method

Parameter	Description	Threshold	Unit
L_{min}	The minimum LAeq,event value	55	dB(A)
E	Difference between LAmax and minimum event value	10	dB(A)
T_{min}	Minimal event duration	5	s
T_{max}	Maximal event duration	120	s
L_{thres}	Level above threshold	60	dB(A)
T_{thres}	Time above level threshold	3	s

2.4 Detection Algorithm - Sound Localization

Medusa sensors allowed us to add an additional layer to the threshold detection system by incorporating data on sound localization. Every 0.1 second, the sensors recorded the dominant sound's elevation (-90° to 90°) and azimuth (-180° to 180°) [3]. The sensor also captures, every 15 minutes, an immersive view from the medusa (Figure 3). From this data, an algorithm was developed to filter noise events that didn't come from the rail tracks by adding a ratio between the time that the sensor localizes the sound inside the railway zone and the duration of the event. Furthermore, the precision of the sensor allowed us to have a filter for different rail tracks, creating the possibility to know the track used for each pass-by.

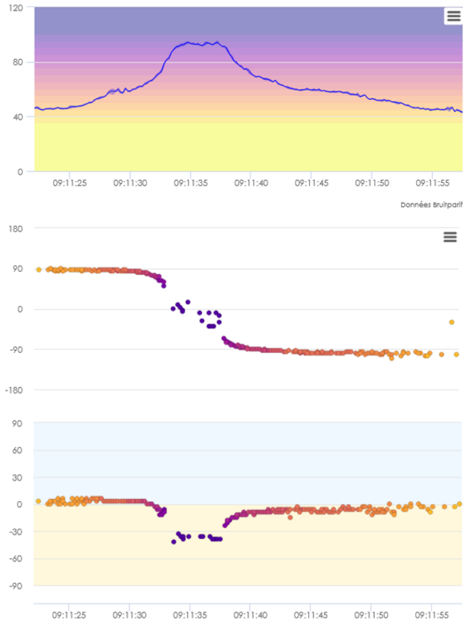

Figure 3 : Data from Medusa 2 during a train pass-by.

2.5 Data Collection and Analysis

Data was collected continuously over a period of three months at each sensor location (April 2023 to July 2023). Every 0.1 second, the sensors recorded the dominant sound level (in dB(A)) along with the corresponding sound direction. The data were stored in a central database for post-processing and analysis.
To analyze the results of the automatic detection events, the accuracy was compared to the rail traffic data from SNCF Reseau and to the video recording added with the medusa sensor from the Genifer study [3]. This allowed cross-reference the effectiveness of the method to detect trains events and more information such as train track.
The first step in the analysis was to detect all sound events using threshold methods, then to use localization filtering data for each event in the railway zone.
Finally, the last step consisted of separating the railway tracks into two zones, south (V1B and EV1 tracks) and north (V2B,V2 and V1 tracks). We filtered the events coming from the south zone with the Medusa 1 and from the north zone with Medusa 2. This allowed us to compare the accuracy of medusa's localization data with the cameras.

3. RESULTS

3.1 Railway Noise Event Detection

During the three-month monitoring period (April 2023 to July 2023), continuous sound data were collected by the two Medusa sensors, capturing the dominant sound levels every 100 ms. Two different detection algorithms were tested: the Butterworth method and the LA50 + 5 method.
For Medusa 1, the Butterworth method detected an average of 552 noise events per day, while the LA50 + 5 method identified 511 events per day. In comparison, Medusa 2 registered higher daily event counts: 824 for the Butterworth method and 876 for the LA50 + 5 method. However, these initial results significantly exceeded the expected train count, as SNCF Réseau's traffic dataset indicated an average of 354 train pass-by per day (Table 3).
To refine the detection and align it more closely with actual train events, a sound localization filter was applied. This filtering step dramatically reduced the number of detected events. Medusa's event count dropped by over 40%, resulting in 311 events per day for the Butterworth method and 294 events per day for the LA50 + 5 method. Medusa 2 showed a reduction of approximately 60%, yielding 327 filtered events per day for both detection methods.
When compared to the video camera automatic detection during the day (6h-22h), Medusa 1 detected only trains passing through the tracks V1B, and EV1 and medusa 2 detected the trains passing through the tracks V2B, V2, and V1, the precision of the detection for both methods was higher than 0.95 and the sensitivity higher than 0.98 (Table 4).

3.2 Track Classification

In addition, to detecting railway noise events, the medusa sensors provided valuable information regarding the track of each pass-by. 2692 video clips were reviewed by hand in the Genifer study [3]. This data has been used to compare the accuracy of the medusa sensor to detect the right track.
The Butterworth-based detection method correctly identified 2,510 events out of 2,692, resulting in a precision of 0.93 (Table 5). Similarly, the LA50 + 5 method achieved slightly higher accuracy, with 2,542 correct detections and a precision of 0.94. False negatives, representing train pass-by that were not matched to the correct track, were slightly higher for the Butterworth method (182 events) compared to the LA50 + 5 method (150 events).

4. DISCUSSION AND CONCLUSION

This study demonstrates the feasibility and effectiveness of using Medusa sensors for detecting railway noise events and identifying train tracks in a complex urban environment. The two detection algorithms tested—Butterworth and LA50 + 5—showed great performance, with both achieving precision values exceeding 0.95 and sensitivity values above 0.98 when compared to video-based validation.

Track classification performance was also strong, with the LA50 + 5 method slightly outperforming the Butterworth method in terms of precision (0.94 vs. 0.93).

Compared to machine learning methods [6,7,8,12], this approach does not rely on extensive audio datasets and allows for near-real time data, making it more adaptable to long-term monitoring applications while complying with data privacy regulations.

However, some limitations were noted. The false negatives show the difficulty to distinguish adjacent tracks, especially during simultaneous trains pass-by. Indeed, further research is needed to study the potential of incorporating advanced machine learning techniques or additional localization parameters to further improve track differentiation

Finally, more research is needed to explore the possibility of using localization data to estimate train speed.

TABLE 3. Events detection method results before (raw) and after (filtered) filtering with localization data

Sensor	Method	Period			
		6:00-18:00	18:00-22:00	22:00-6:00	24h
Medusa 1	*Butterworth*				
	raw	345	137	70	552
	filtered	197	77	37	311
Medusa 1	*LA50 + 5*				
	raw	323	125	63	511
	filtered	188	73	33	294
Medusa 2	*Butterworth*				
	raw	553	182	89	824
	filtered	206	81	40	327
Medusa 2	*LA50 + 5*				
	raw	598	197	81	876
	filtered	208	81	38	327
SNCF	***O.R.E***				
	Traffic	**225**	**89**	**40**	**354**

TABLE 4. Detection Accuracy of Train Events (Filtered Data, Daytime Only) Compared to Video Recordings.

		True Positive	False Positive	False Negative	Precision	Sensitivity
Medusas						
	butterworth	16551	605	130	0.96	0.99
	LA50 + 5	16430	841	251	0.95	0.98

TABLE 5. Track Detection Accuracy Compared to Video Recordings.

		True Positive	False Negative	Precision
Medusas				
	butterworth	2510	182	0.93
	LA50 + 5	2542	150	0.94

5. ACKNOWLEDGMENTS

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