Journal of Engineering and Computer Sciences
Vol. 16, No. 2, pp. 1-18 (Jul 2024)

Acoustic Traffic Sign Recognition: A Computationally Efficient Alternative to Image-Based Detection

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[Received: 6 Mar 2025, Revised: 17 Jun 2025, Accepted: 9 Jul 2025, Published Sep 2025]

Abstract: Autonomous vehicles rely heavily on image processing techniques for traffic sign recognition, yet these approaches face significant challenges due to environmental conditions, occlusions, and high computational demands. To address these limitations, this paper introduces a novel acoustic-based approach named Noise Pattern Recognition (NPR) system that utilizes sound-based detection to enhance road awareness for autonomous vehicles. Instead of relying on visual inputs, our approach encodes traffic sign information through specially designed road bumps that generate distinct noise patterns when vehicles pass over them. These acoustic patterns, structured similarly to Morse code, are captured by onboard microphones, processed using signal analysis techniques, and converted into binary sequences that correspond to specific traffic signs. The proposed system consists of three key components: a sound recording module, a signal processing module, and a transmission module that relays detected traffic sign information to the vehicle's control system. Simulation results show the feasibility of this method by demonstrating its robustness against environmental interference and its ability to operate efficiently with minimal computational resources.

Keywords: Autonomous vehicles; Traffic sign recognition; Noise pattern recognition; Sound-based detection; Signal processing

1. INTRODUCTION

An autonomous vehicle is an emerging technology with considerable potential for significant benefits, which has witnessed a rising demand in recent years. The concept of autonomous vehicles has deep historical roots, dating back to the early 1900s when inventor Francis Houdina demonstrated the remote control of a car through radio signals, initiating the engine and steering [1]. This early experiment marked a glimpse into the future, with subsequent experiments, such as [1]. RCA labs guided cars in the fifties and sixties, further exploring the possibilities [2].

The 1960s brought a novel approach, introducing the idea of integrating cameras into autonomous vehicles and programming them to recognize and follow lines on the ground, similar

to the principles used in space technology [3]. This innovation has become a crucial aspect of the contemporary autonomous vehicle industry, showcasing the evolution of this technology over time. Today, autonomous vehicles are not only feasible but are also considered a safe and viable choice for various applications.

Over the recent years, vehicles have incorporated several semi-automated features, including lane-keeping assistance, backup cameras, and automatic braking systems. An autonomous vehicle can be defined as a vehicle that functions independently of human input, utilizes sophisticated sensors to perceive its environment, and identifies obstacles in its path. The data collected by these sensors is then processed by an onboard computer, enabling the vehicle to take appropriate actions to ensure a secure driving experience without the need for human intervention. [4]

Artificial intelligence (AI) and the Internet of Things (IoT) are crucial in advancing the progress of autonomous vehicles.

Also referred to as self-driving cars, these vehicles can navigate and operate without drivers. They employ various sensors and technologies to collect data about their surroundings and autonomously decide on movements and responses in diverse situations. The integration of AI and IoT devices contributes significantly to enhancing the safety, efficiency, and convenience of autonomous vehicles for passengers [5], [6].

Autonomous vehicles rely on various sensors and technologies, such as radar, lidar, and cameras, to drive and make decisions. These sensors produce a substantial amount of data that needs to be transmitted to the vehicle's onboard or remote computer for processing. This data is crucial for the computer to make informed decisions regarding the vehicle's movements. The effectiveness of these sensors is heavily dependent on connectivity, and the introduction of fifth generation (5G) is instrumental in this regard. The ultra-reliable and low-latency communications provided by 5G facilitate the transmission of data at significantly higher speeds and with minimal delays. This capability has the potential to enable autonomous vehicles to respond more swiftly and accurately to their surroundings [7].

Detecting traffic signs is an essential part of autonomous vehicle technology as it allows vehicles to respond to road signs and traffic signals appropriately, ensuring safe and lawful travel. Typically, image processing algorithms are employed to identify traffic signs in images captured by the vehicle's cameras. These algorithms often utilize techniques like feature extraction and object identification to determine the presence and type of traffic signs in the images [8]. Upon detecting a traffic sign, the autonomous vehicle can use this information to make informed decisions. For instance, if a stop sign is recognized, the vehicle may come to a stop before proceeding through the intersection. Similarly, if a speed limit sign is detected, the vehicle can adjust its speed accordingly. However, utilizing image processing in detecting traffic signs can cause several problems in autonomous vehicles. For instance [9]– [11]:

- Variability in the appearance of traffic signs, which can differ in size, shape, and layout.
- Lighting challenges arise from variations in quality and appearance due to different lighting conditions, such as day or night, and the use of diverse light sources.
- Limited field of view, as autonomous vehicles typically have constrained visibility, preventing them from observing all traffic signs in their environment simultaneously.
- Obstacles such as occlusion, damage, similarity, and other factors can further complicate the accurate detection of traffic signs.

Therefore, image-based approaches for detecting traffic signs and providing awareness to Autonomous vehicles are considered to be problematic. Additionally, image processing requires high computation capabilities, which can be costly if implemented inside the vehicle or may suffer from latency issues if implemented in the cloud. Given these challenges, it is crucial to employ an alternative approach for conveying road information to autonomous vehicles that does not rely on the image processing of traffic signs. Consequently, this paper introduces a novel method designed to enhance the awareness of autonomous vehicles regarding the status of the road, namely, noise pattern recognition (NPR). This method involves a combination of distinct road bumps, Morse code, and simple signal processing techniques.

NPR is used in traffic management systems where road bumps are designed not just for speed control but also to generate specific sound patterns. These road bumps, engineered with varying shapes, sizes, and surface textures, can produce distinct noise patterns when vehicles pass over them.

Each type of road bump is associated with a particular noise pattern. For example, a road bump near a ”Stop” sign might produce a different sound compared to one near a” Yield” sign or a ”Speed Limit” sign. The idea is that as a vehicle drives over these bumps, the resulting sound or vibration is unique to that bump.

This sound pattern is then captured by sensors or microphones placed near the bump. Once recorded, the sound is processed to recognize and classify the noise pattern. Then the sound is analyzed to reveal the characteristics of the sound, such as amplitude and duration, to determine which specific road sign it corresponds to.

The advantage of this system is to create an additional layer of road safety and communication. For example, in low-visibility conditions or areas where traditional signs might be obstructed, the NPR system can ensure that the traffic rules are still communicated effectively to drivers. The distinct noise patterns can serve as audible reminders or alerts for drivers, potentially reducing accidents and enhancing overall road safety. One of the most significant advantages for NPR is that sound-based signal analysis requires much less computational resources compared to vision analysis, which also requires less complex hardware.

2. LITERATURE REVIEW

Over the past several years, a substantial number of research papers have been published addressing various methods for traffic sign detection. A majority of these studies emphasize the use of image processing techniques, which play a central role in the detection and recognition of road signs. These approaches incorporate a diverse range of methodologies; each tailored to specific aspects of the detection process.

The body of research on traffic sign detection can generally be divided into two primary categories: image-based methods and alternative approaches. Within image-based detection, two main methodological directions emerge: machine learning-based techniques and deep learning methods.

For machine learning-based approaches, several studies emphasize image segmentation to isolate relevant regions in an image, thereby simplifying and speeding up the detection process [12]. For example, [13] introduced a machine learning model utilizing Support Vector Machines (SVM) combined with Histogram of Oriented Gradients (HOG) to detect prohibitory traffic signs. Similarly, [14] proposed a two-stage pipeline involving image enhancement using Laplace and Gaussian filters, followed by classification through SVM and HOG features. Another study [15] employed Hough Transform for detecting circular speed limit signs and used multi-Class SVM for recognizing speed values, achieving 93% accuracy and demonstrating real-time applicability in autonomous and driver-assist systems.

Beyond segmentation and classical classification, some works leverage machine learning and deep learning to classify signs based on visual attributes such as shape and color [16]– [19]. More advanced techniques focus on recognizing partially or fully obscured signs, improving reliability under difficult conditions [20]. For instance, [21] applied SVM to enhance traffic sign recognition accuracy further.

The authors of [20] address the challenge of detecting traffic signs that are fully or partially obscured by introducing an innovative algorithm. This algorithm builds upon traditional color-based detection methods, aiming to improve detection accuracy. The proposed approach was tested in a moving vehicle under varying speeds, demonstrating a significant improvement in accuracy, with an increase of approximately 15%. In [22], the authors propose a two-stage method, the first is for traffic sign detection using image processing and an ensemble of Convolutional Neural Networks for classification.

On the other hand, numerous studies have adopted deep learning techniques for traffic sign detection. For instance, the study in [23] employs Region-based Convolutional Neural Networks (R-CNN), using a two-stage pipeline: first generating region proposals where traffic signs are likely to appear, then classifying those regions using a CNN. This method is designed to enhance both the accuracy and efficiency of traffic sign recognition, making it particularly suitable for autonomous driving and advanced driver-assistance systems.

Similarly, the authors of [24] use a LeNet-based Convolutional Neural Network to detect German traffic signs and further convert recognized signs into audio outputs to improve driver awareness.

YOLO (You Only Look Once) is a real-time object detection algorithm widely used in traffic sign detection due to its high speed and accuracy [25]– [27], making it ideal for autonomous driving and advanced driver-assistance systems. In [25], the focus shifts to detecting small-scale traffic signs-typically distant signs that appear smaller in images-using YOLOv7. The novelty lies in leveraging YOLOv7's capabilities to address the challenge of recognizing such small objects effectively. The work in [26] investigates the use of the YOLO algorithm for traffic sign detection on Taiwanese roads. By combining datasets and evaluating both YOLOv5s6 and YOLOv8s, the study aims to boost detection performance for local sign types. Lastly, [27] introduces RD-YOLO, an improved version of YOLOv5 tailored for roadside perception.

This model significantly enhances small object detection, achieving a 5.5% boost in precision while reducing the model's size by 55%, making it more efficient for real-time deployment.

The second major category in traffic sign detection research involves alternative, non-visual detection methods, which do not rely on traditional image processing. While still emerging and less extensively studied, these approaches offer advantages in computational efficiency and show promising results. For instance, the authors of [28] employed LiDAR data to detect traffic signs and evaluate their visibility, utilizing geometric and reflectance characteristics for detection and spatial-visual features for visibility estimation. Their method, validated on real-world data, demonstrated strong potential for intelligent transportation systems. Similarly, the paper [29] reviewed the use of Mobile Laser Scanning (MLS) in extracting road features such as lane markings and roadside infrastructure, underscoring LiDAR's value in road safety analysis and asset management despite the challenges of handling large-scale point cloud datasets. Furthermore, [30] proposed integrating acoustic sensing with image processing to enhance autonomous vehicle (AV) safety. Their approach addresses the need for AVs to interpret horn and siren signals commonly used by human drivers, advocating for the inclusion of acoustic sensors to facilitate more responsive and context-aware navigation.

These alternative detection strategies reflect a growing interest in leveraging non-visual modalities to overcome the limitations of image-based systems, particularly in complex or low-visibility environments. Our proposed method falls within this category, introducing a sound-based traffic sign detection system that utilizes noise patterns generated by specifically designed road bumps. By avoiding the high computational demands and visual limitations of image processing, our approach offers a lightweight and efficient solution, making it highly suitable for real-time deployment in autonomous vehicles and smart transportation systems.

3. System Model

This section presents and details a system model to outline the procedure for the NPR.

1. *The Design of the NPR System*

This system model aims to enhance traffic sign detection for autonomous vehicles by shifting from image processing to sound-based detection using Morse code and road bumps. This work is primarily experimental, with real-world tests conducted to evaluate the system's effectiveness in practical driving scenarios, including the use of actual vehicles, microphones, and signal processing hardware. The model is composed of three main modules.

- Sound Recording Module: This module records sounds generated by the vehicle as it passes over specific road bumps. Each bump creates a unique sound, correlating to different traffic signs through a Morse code-like binary system.
- Signal Processing Module: This module processes the recorded audio, segments it based on time intervals, and analyzes it to identify distinct" dashes" (short-distance bumps that generate sounds mimicking the long dash sound) and "dots" (fewer bumps that generate sound that mimics the "dot" sound). Converting them into binary sequences. These sequences are then matched to specific traffic signs.
- Transmission Module: After identifying the traffic sign based on the sound pattern, this module transmits the information to the vehicle's control system, which then integrates it for navigation or alerts the driver.

The system's design leverages sound detection to overcome limitations of visual sign recognition, particularly in challenging environments like desert areas where signs may be obscured. Using Morse code as a framework provides a low-complexity, robust alternative, making the model more computationally efficient and resilient against environmental interference.

More specifically, the model comprises four components:

1. Road bumps are specifically designed to produce intended noise.
2. Sensors embedded within autonomous vehicles (AVs) to perceive the noise generated by the bumps.
3. A computational unit integrated within the AV to analyze the data and relay decisions to the vehicle.
4. A display positioned near the driver to show the identified signals.

The combination of the sound recording, signal processing, and transmission will form a reliable and cost-effective system for detecting traffic signs and providing awareness to autonomous vehicles. This will work to capture and analyze the sound waves generated by road bumps and transmit the extracted information to the autonomous vehicle for safe navigation. This system is designed to be reliable and efficient in detecting traffic signs while avoiding the limitations of traditional image processing approaches, such as high costs or weather-related issues. Figure 1 presents a unified illustration that combines the overall system architecture and the design of the rumble strips into a single figure with two distinct parts. The first part of the figure outlines the proposed system model, which enables an AV to detect traffic signs through sound-based interpretation rather than conventional image processing. This innovative approach relies on specially engineered road bumps that generate unique acoustic patterns as vehicles pass over them. These sound patterns, captured by onboard microphones, are then analyzed to identify encoded traffic information.

The second part of Figure 1 provides a detailed depiction of the rumble strip layout. Each traffic sign is associated with a specific sequence of bumps arranged to produce a recognizable pattern.

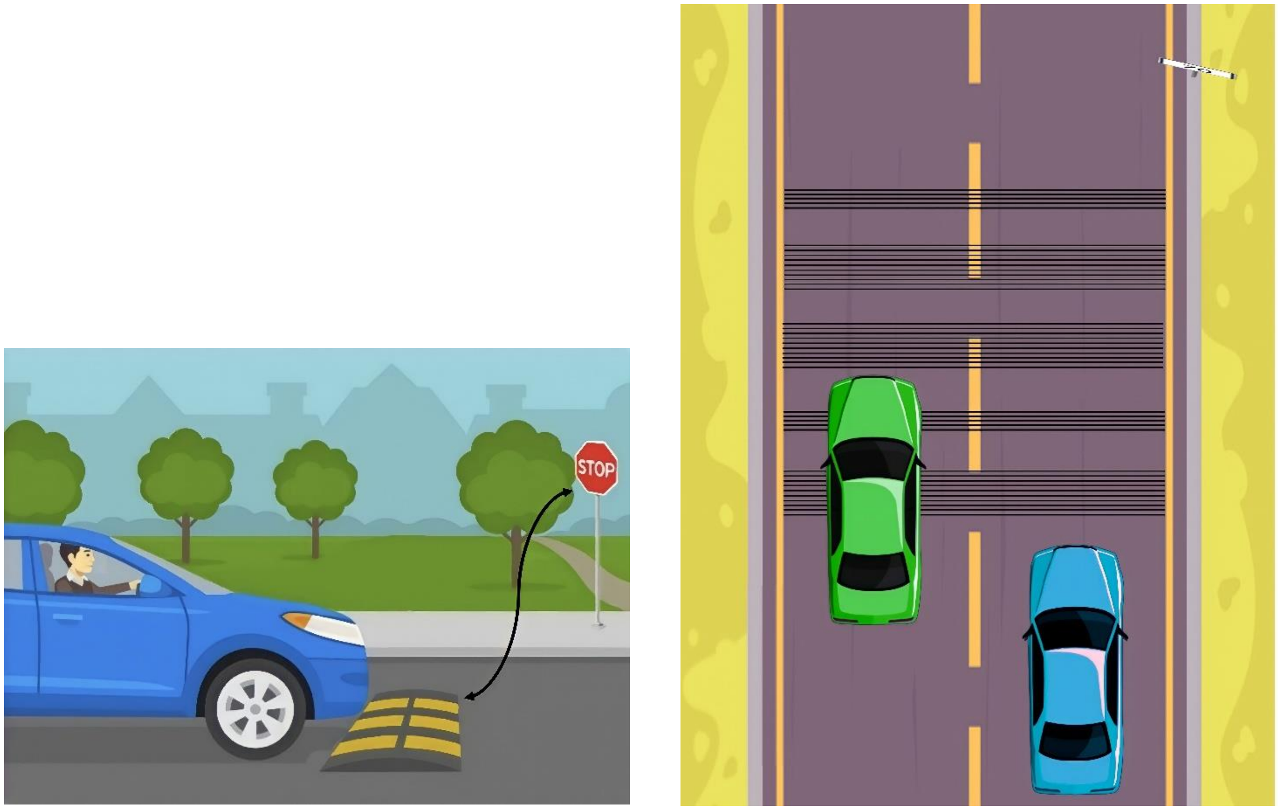

Fig. 1: Design for sound-based traffic sign detection bumps using Morse code-inspired acoustic patterns.

Sound pattern, analogous to Morse code. As the AV traverses these strips, the resulting acoustic signal, characterized by variations in amplitude and duration, is recorded and processed into binary sequences. These sequences are subsequently matched against a predefined database to identify the corresponding traffic sign.

It is important to note that this system does not require the development of entirely new physical road features. Instead, it utilizes rumble strips, which are a pre-existing and widely implemented road safety element that is designed to produce audible and tactile feedback when vehicles drive over them. These strips are commonly found near intersections, sharp turns, or roadside hazards. In the context of this study, pre-installed rumble strips were utilized to simulate Morse-code-like acoustic signals. By controlling their spacing and frequency, they serve as a medium to encode traffic sign information without the need for major infrastructure changes. This approach ensures the system's feasibility and practicality by relying on standard road components rather than introducing new, costly installations.

2. *Sound-Based Traffic Sign Detection Algorithm*

Algorithm 1 Sound-Based Traffic Sign Detection System

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1. **Start**
2. Initialize the system parameters: τ and λ_{th}.
3. **While** AV is moving, **do**
4. **Part 1:** Detect Sound from Bumps.
5. Continuously monitor audio input from the microphone.
6. **If** Detected sound $\geq \lambda_{th}$ **then**
7. Record audio for τ seconds.
8. **end if**
9. **Part 2:** Process Recorded Sound.
10. Split the recorded audio into segments based on expected bump intervals.
11. **For each** segment, **do**
12. Measure amplitude to distinguish between a `dash` (high amplitude) and a `dot` (low amplitude).
13. Generate binary sequence:
    - Assign `1` for long sound.
    - Assign `0` for short sound.
14. **end for**
15. **Part 3:** Map Binary Sequence to Traffic Sign.
16. Compare the generated binary sequence to the database of traffic sign codes.
17. Identify the traffic sign matching the sequence.
18. **Part 4:** Transmit Traffic Sign Data.
19. Send identified traffic sign information to the vehicle's control system.
20. Display or log traffic sign for navigation purposes.
21. **end while**
22. **Part 5:** Test and optimize.
23. Conduct tests to validate:
    - Accuracy of sound detection and binary matching.
    - Precision in matching binary codes to traffic signs.
24. Adjust λ, τ, and database entries for improvement.
25. **End**
26. Stop detection when the vehicle is inactive or monitoring is not required.

Algorithm 1 outlines the procedure for recording and analyzing detected sounds. The algorithm is divided into five parts, each performing a distinct function. Part 1 focuses on identifying road speed bumps, where a microphone remains continuously active, monitoring and recording. When a sound is detected with an amplitude exceeding the threshold λ_{th}, it triggers recording for a period of τ, after which the sound is stored. Part 2 details the procedure for analyzing the recorded sound by breaking it down into manageable segments and interpreting the data to identify binary values. The process begins by dividing the entire recorded duration into smaller, time-specific segments that correlate to each speed bump's duration. Each segment is then individually assessed to determine whether it signifies a binary '1' or '0'. This binary classification is based on the length of the sound within each segment: segments with a prolonged sound duration are classified as '1', indicating a substantial or prolonged sound signal associated with a speed bump. In contrast, segments with shorter or brief sounds are classified as '0', representing gaps or minimal sound impact between bumps. This approach effectively transforms the continuous sound data into a binary sequence, where each segment corresponds to either a '1' or '0' depending on the characteristics of the recorded sound. The result is a binary sequence that can be further analyzed or matched to predefined patterns for sign interpretation or other functions within the system.

Part 3 involves mapping the generated binary sequence to a specific traffic sign by comparing it with stored patterns in a database. This is achieved by matching the binary sequence produced during sound processing with pre-existing binary patterns that correspond to known traffic signs. When a match is found, the system identifies and associates the binary sequence with the relevant traffic sign. If no match is detected, it suggests that the recorded sound may have originated from road bumps that are unrelated to traffic signs in the system, possibly due to random noise or non-standard road features. This process of verification ensures that only recognized patterns linked to specific traffic signs are interpreted and used, filtering out irrelevant sounds and reducing potential false positives.

Part 4 is responsible for transmitting the interpreted signal, along with the identified traffic sign, to the appropriate system component. This may involve sending the information to a display visible to the driver, allowing them to receive real-time traffic sign updates, or directly transmitting it to the autonomous vehicle's (AV's) central processing unit. In the case of the AV, the processing unit utilizes this data to determine the necessary response, such as adjusting speed, navigating turns, or taking other safety measures. This ensures that the vehicle or driver

can respond promptly and accurately to detected traffic signs, enhancing situational awareness and safety.

Part 5 is dedicated to enhancing the system's overall performance by incorporating feedback from either the AV's processing unit or the driver. This part includes two key stages: Testing and Optimizing.

Testing Stage: In this stage, two main steps are carried out. The first step involves conducting tests to assess the system's accuracy in detecting and matching traffic signs. This validation process checks whether the system correctly identifies traffic signs based on the recorded data. The insights from this step lead to the second step, which refines and improves the system's accuracy in associating detected sounds with specific traffic signs.

Optimization Stage: Here, the system adjusts its parameters to better adapt to the environment. For instance, the amplitude threshold λ is fine-tuned to account for ambient noise levels; it can be increased or decreased to ensure reliable detection of relevant sounds. Additionally, the system optimizes the timing of the recording trigger, ensuring that it captures the start and end of each road bump more precisely. This stage helps the system to remain effective in various driving conditions, improving both detection accuracy and response speed. Finally, the algorithm stops when the vehicle is either inactive or the monitoring is not required.

4. Simulation Results

In this section, we present the outcomes of simulations and real-world tests conducted to evaluate the effectiveness of the sound-based traffic sign detection system in detecting and interpreting road signals. The results illustrate the system's ability to overcome challenges traditionally associated with image-based traffic sign detection, such as environmental interference and computational intensity.

The experimental setup used to validate the proposed system is summarized in Table I. This configuration was designed to assess the system's performance. The main component is the Raspberry Pi 4 Model B, which handles all signal processing tasks, including audio segmentation and traffic sign decoding. Acoustic signals were captured using an omnidirectional microphone. The interpreted traffic signs were displayed in real-time on an LCD screen connected to the Raspberry Pi. Custom-made rumble strips, gathered with varying dimensions and spacing to encode Morse-code-like patterns, served as the source of distinctive acoustic signals. The test vehicle, a standard sedan, was used to drive over these bumps while recording audio from

different microphone placements. Supporting components, including a power supply unit, a MicroSD card for software deployment, and protective mounts for securing the microphone in multiple positions, were also part of the experimental configuration. This setup enabled comprehensive testing of the NPR system's ability to detect, process, and interpret traffic signs based solely on road-induced acoustic cues.

Table 1: Hardware Components Used in Experimental Setup

Component	Specification
Raspberry Pi 4 Model B	Signal processing and system control
Microphone	Generic omnidirectional microphone for audio capture
LCD Display Module	Displays interpreted traffic sign information.
Custom Rumble Strips	Bump design to simulate Morse code dot/dash patterns
Power Supply Unit	Provides power to the Raspberry Pi and the microphone
Vehicle (Standard Sedan)	Used for driving over bumps and generating sound patterns
MicroSD Card (32GB)	Stores operating system and signal processing scripts
Protective Mounts	Used to fix the microphone in different positions on the vehicle

The experiment was conducted to evaluate the effectiveness of the NPR using pre-installed rumble strips. A standard passenger vehicle equipped with a microphone and Raspberry Pi was used to capture the acoustic signals generated as the vehicle passed over the bumps. The microphone was tested in four different positions: near the front bumper, inside the cabin, in the trunk, and near the rear tire. Each location presented unique noise characteristics, with the rear tire position providing the clearest signal and the least interference from engine noise. Audio data was recorded at a sampling rate of 44.1 kHz, and each crossing generated a short audio segment (2–3 seconds). The recordings were processed to extract peak amplitude values, which were then analyzed across a range of detection thresholds from 0.1 to 1.0. The primary performance metric was the probability of miss detection, calculated as the ratio of undetected events (amplitudes below threshold) to the total number of events for each microphone position. In the first experiment, we investigated the impact of surrounding noise on the system's performance. Given that the system relies on sound recordings, it is inherently susceptible to interference from various noise sources around the vehicle. The environment during testing is particularly noisy due to multiple factors, such as the vehicle's engine, road irregularities like manholes, and the presence of other moving vehicles, among other noise-generating elements.

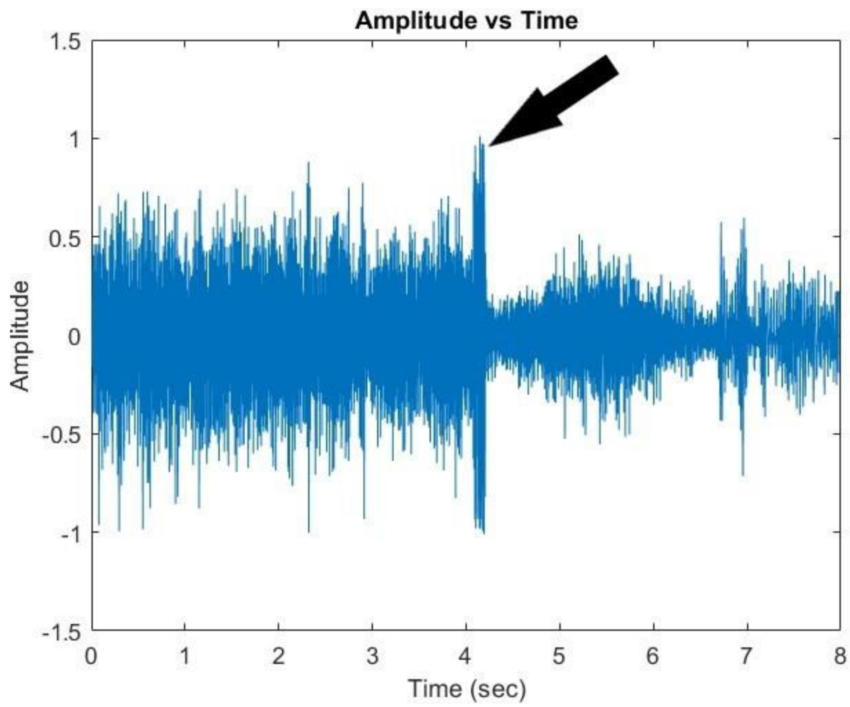

Fig. 2: The microphone is positioned at the front of the vehicle.

To address this challenge, we tested the system in four different locations on the vehicle to identify the position with the least noise interference. The first location was near one of the front tires, at the front of the vehicle. The second was inside the vehicle, specifically at the front passenger seat. The third location was in the trunk, which provided a more enclosed setting. Finally, the fourth location was at the rear of the vehicle, close to the right back tire. By comparing the noise levels across these locations, we aim to determine the optimal placement for the microphone to ensure accurate sound detection and minimize the impact of environmental noise.

In Figure 2, the microphone is positioned at the front of the vehicle to evaluate the noise generated while driving over a series of rumble strips multiple times. As illustrated in the figure, the black arrow indicates the point where the vehicle passes over the rumble strip. The results reveal that this location is significantly affected by high levels of background noise, primarily due to its proximity to the vehicle's engine. The engine produces a substantial amount of ambient noise, which overwhelms the sound generated by the rumble strips.

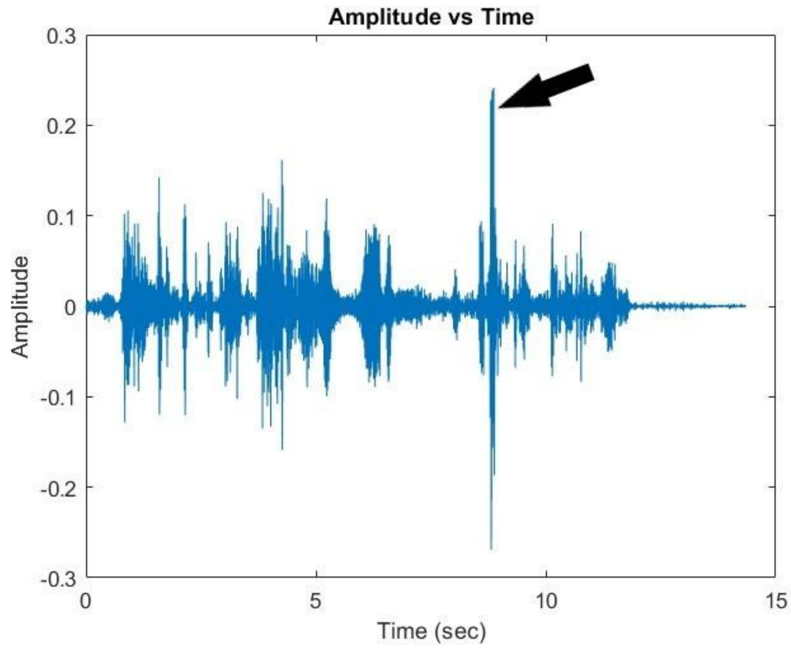

Fig. 3: The microphone is positioned in the trunk of the vehicle.

This observation highlights a critical drawback of this microphone placement: the excessive background noise severely impacts the system's ability to distinguish the specific sound patterns associated with the rumble strips. Consequently, this location proves to be unsuitable for the microphone, as it fails to provide a clear and reliable audio signal for accurate detection and analysis of traffic-related sound patterns.

In Figure 3, the microphone is positioned inside the trunk of the vehicle to evaluate its effectiveness in capturing the sound generated by rumble strips. This location offers a degree of isolation for the microphone, distancing it from the vehicle's engine and reducing the direct impact of engine noise. However, the design of the trunk introduces new challenges. While it isolates external noise to some extent, it also dampens and distorts the sound signals produced by the rumble strips.

As illustrated in the figure, there is a noticeable spike corresponding to the rumble strips when the vehicle drives over them. However, the amplitude of this spike is relatively low compared to the background noise levels. This indicates that while the trunk provides some protection from engine noise and other environmental sounds, it simultaneously diminishes the clarity and prominence of the rumble strip-generated sounds.

Figure 4 illustrates the behavior of the microphone when positioned inside the vehicle. In this location, the microphone benefits from being isolated from external environmental noise, such as engine sounds or road noise, allowing it to detect the noise generated by rumble strips with greater clarity. However, this setup introduces a new challenge: susceptibility to interior noises. These include sounds such as conversations, music, or other human-generated noises within the vehicle cabin.

As shown in the figure, there is a distinct spike corresponding to the sound produced by the rumble strips, as indicated by the arrow. However, a previous spike of greater amplitude, caused by interior noise, can be seen in the data. This larger spike has the potential to mislead the system by overshadowing the desired signal. Without manual intervention or advanced filtering techniques, the system may struggle to differentiate between the rumble strip-generated sounds and other noise sources within the cabin.

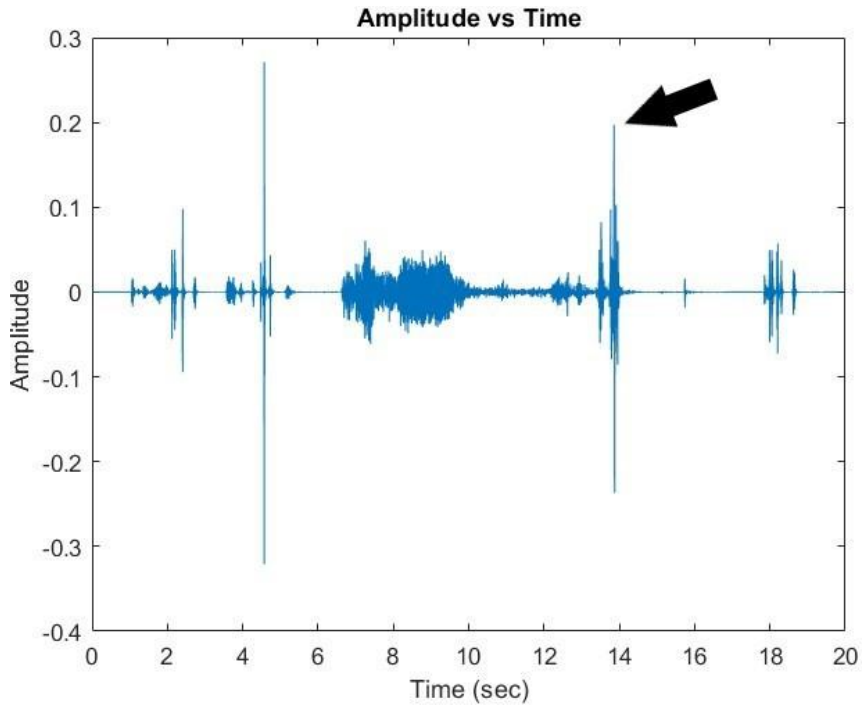

Fig. 4: The microphone is positioned inside the vehicle.

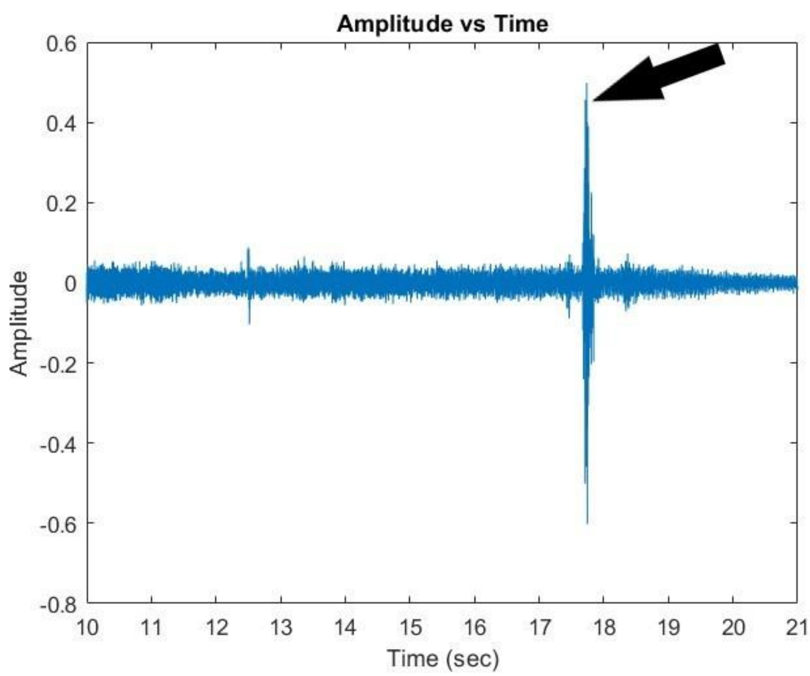

Fig. 5: The microphone is positioned at the rear of the vehicle.

Figure 5 illustrates the performance of the microphone when positioned at the rear of the vehicle, near the right tire. This placement proves to be the most effective among the tested locations. As shown in the figure, the surrounding environmental noise is minimal, allowing for a clean audio signal. Additionally, a prominent and distinct spike is observed in the data, clearly corresponding to the noise generated by the rumble strip.

This optimal performance can be attributed to the placement of the microphone. Being at the back of the car, it is significantly distanced from the engine, which is a primary source of background noise. Simultaneously, its proximity to the tire allows it to capture the rumble strip-generated sound with great clarity and precision. This combination of reduced interference and enhanced signal detection makes the rear tire area an ideal location for the microphone. When the microphone is positioned at the rear of the vehicle, the following figure evaluates the maximum and minimum amplitude of the sound generated as the vehicle passes over the rumble strip. The data presented in the figure shows that the amplitude values range between 0.3 and 0.55. Based on these findings, the detection threshold for sound noise should be set with both a lower limit of 0.3 and an upper limit of 0.6.

This dual threshold ensures that the system reliably detects the sound patterns produced by the rumble strips while filtering out lower-amplitude background noises and higher-amplitude noises that exceed the expected range. By implementing this upper limit, the system minimizes false positives caused by unexpected loud noises, enhancing the accuracy and robustness of its detection capabilities.

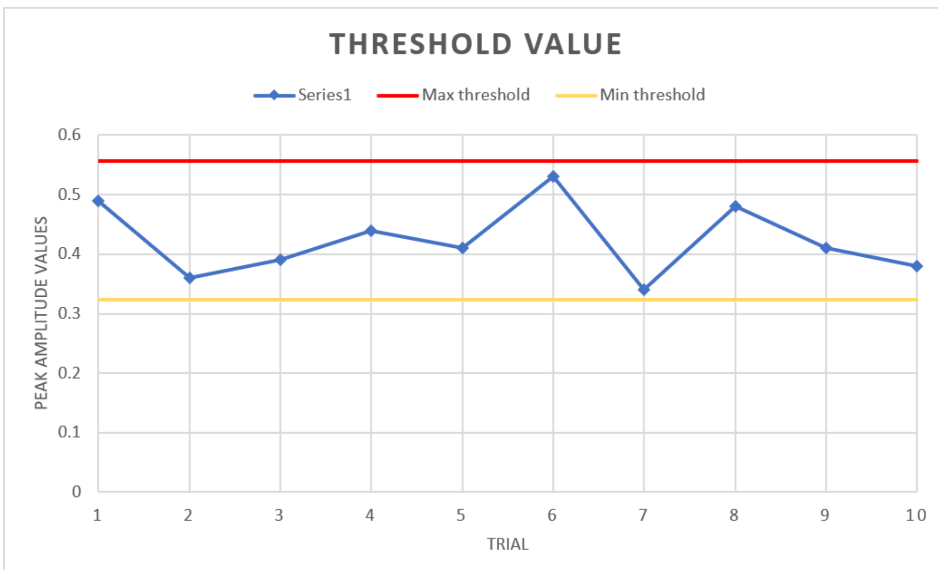

Fig. 6: The maximum and minimum sound levels generated by the bumps.

Figure 7 illustrates the relationship between the detection threshold (λ) and the probability of miss detection across different microphone placement locations on the vehicle. The x-axis represents the detection threshold, λ, ranging from 0.1 to 1.0 in normalized amplitude units. This threshold determines the minimum signal strength required for the system to consider a sound event, such as that produced by a rumble strip, as valid. As λ increases, the system becomes more conservative, meaning it requires a stronger signal to register a detection.

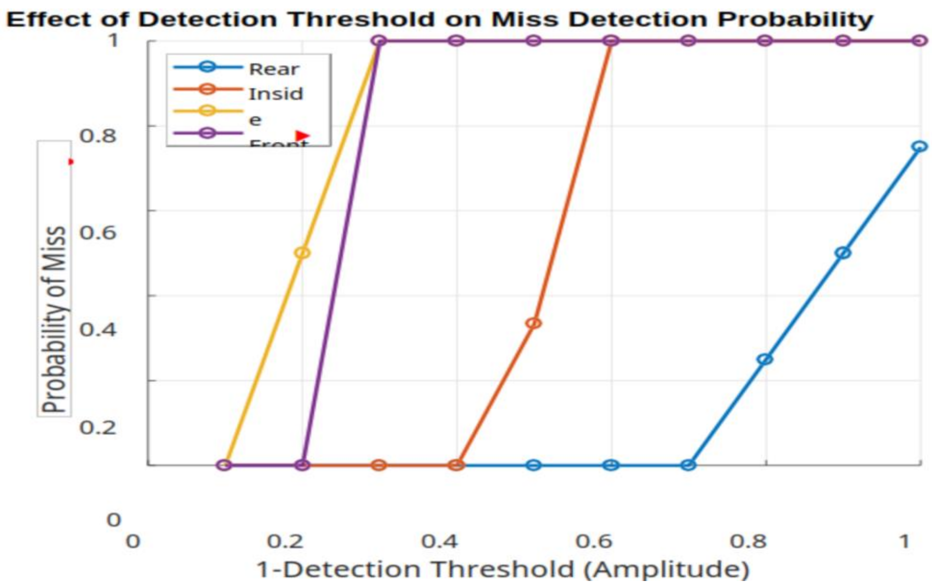

Fig. 7: The probability of missing detection for each location.

The y-axis presents the probability of miss detection, defined as the ratio of true events (i.e., vehicle passing over a rumble strip) that failed to exceed the set threshold. This metric reflects how often valid acoustic signals are ignored by the system due to insufficient amplitude. For each microphone position tested (e.g., front tire, trunk, cabin, rear tire), this figure provides insight into how sensitivity to signal strength varies depending on ambient noise and structural placement.

As shown in the figure, lower threshold values generally yield fewer missed detections, since the system is more permissive in accepting signals. However, this can come at the cost of increased false alarms, which are not shown in this figure but are important to consider. Conversely, higher thresholds reduce false alarms but significantly raise the probability of missing valid signals, especially in noisy environments or suboptimal microphone positions.

Each line in the figure corresponds to one of the four microphone positions: Front, Rear, Inside, and Trunk. As expected, increasing the threshold leads to a higher probability of missed detections, since more events fall below the cutoff point. The figure clearly shows that the rear position consistently achieves the lowest miss detection probability across all thresholds, indicating superior signal clarity and minimal noise interference.

5. Discussion and Future Work

While the proposed NPR system introduces a promising alternative to image-based traffic sign recognition, several important considerations have emerged during the review process that require further discussion and future exploration.

One significant observation relates to the variability of acoustic signals generated by different vehicle types. Since vehicle characteristics such as weight, suspension design, and tire composition can influence the sound produced when passing over rumble strips, we acknowledge that this may affect the system's consistency. Future work will investigate adaptive filtering techniques and vehicle-specific calibration mechanisms to ensure reliable detection performance across a wide range of vehicles.

Additionally, the concern regarding the potential for false positives due to unintended road features such as potholes is valid. To mitigate this, the NPR system employs sequences of consecutively spaced rumble strips that produce structured, Morse-code-like acoustic patterns. These patterns are highly distinguishable from random road irregularities, making misclassification unlikely.

Another area of discussion involves the acoustic impact of the system. Although rumble strips are already widely used and accepted in modern road infrastructure, we acknowledge that minimizing their noise impact is a worthwhile goal. Future research will explore noise-optimized rumble strip designs in collaboration with experts in road engineering and acoustics. However, such efforts are beyond the scope of the current study and require a multidisciplinary approach. It is also important to note that the system does not propose the removal of physical traffic signs. Traditional signs will remain in place to serve both non-autonomous vehicles and as a fallback mechanism in the event of system malfunction (e.g., microphone failure or excessive environmental noise). The objective of this work is to offload the heavy computational burden associated with vision-based detection by introducing a low-complexity alternative that does not eliminate existing safety infrastructure.

Concerns about durability are also valid. While rumble strips may degrade over time, they typically exhibit long service lifespans and are cost-effective to maintain. Compared to traffic signs, which are prone to visual obstructions, fading, and vandalism, rumble strips require less frequent and less expensive maintenance, making them suitable for long-term deployment.

In summary, while the current study establishes a foundational framework for acoustic-based traffic sign recognition, future work will focus on:

1. Expanding validation to a wider range of vehicle types.
2. Enhancing robustness through signal normalization and machine learning.
3. Exploring infrastructure-aware designs to reduce acoustic impact.
4. Exploring ways to improve the detection rate and minimize the false alarm.

6. Conclusion

This paper presents a novel NPR system that leverages acoustic-based detection for traffic sign recognition, offering an alternative to traditional image-processing techniques used in autonomous vehicles. By designing road bumps to generate unique sound patterns that encode traffic sign information, the proposed system enhances road awareness while addressing key challenges associated with vision-based detection, such as occlusions, environmental variations, and high computational costs. The results from simulations and real-world tests indicate that NPR is a feasible, cost-effective, and computationally efficient approach, particularly in challenging environments where visual sign detection may be unreliable. By integrating NPR into autonomous vehicle systems, real-time traffic sign recognition can be enhanced, ensuring safer and more efficient navigation. The findings suggest that sound-based detection can complement existing vision-based systems, providing an additional layer of robustness in conditions where image processing struggles, such as fog, heavy rain, or obscured signage.

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التعرف الصوتي على إشارات المرور: بديل حاسوبي فعال للكشف القائم على الصور

ملخص: تعتمد المركبات ذاتية القيادة بشكل كبير على تقنيات معالجة الصور للتعرف على إشارات المرور، إلا أن هذه الأساليب تواجه تحديات كبيرة بسبب الظروف البيئية، والانسدادات، والمتطلبات الحسابية العالية. ولمعالجة هذه القيود، تقدم هذه الورقة البحثية نهجًا صوتيًا جديدًا يُسمى نظام التعرف على أنماط الضوضاء (NPR)، والذي يستخدم الكشف الصوتي لتعزيز وعي المركبات ذاتية القيادة بالطريق. فبدلًا من الاعتماد على المدخلات البصرية، يقوم نهجنا بترميز معلومات إشارات المرور من خلال مطبات طريق مصممة خصيصًا تُولد أنماط ضوضاء مميزة عند مرور المركبات فوقها. تُلتقط هذه الأنماط الصوتية، المُصممة على غرار شفرة مورس، بواسطة ميكروفونات مدمجة، وتُعالج باستخدام تقنيات تحليل الإشارات، وتُحول إلى تسلسلات ثنائية تتوافق مع إشارات مرور محددة. يتكون النظام المقترح من ثلاثة مكونات رئيسية: وحدة تسجيل صوت، ووحدة معالجة إشارات، ووحدة إرسال تنقل معلومات إشارات المرور المكتشفة إلى نظام التحكم في المركبة. تُظهر نتائج المحاكاة جدوى هذه الطريقة، من خلال إثبات متانتها في مواجهة التداخل البيئي وقدرتها على العمل بكفاءة مع الحد الأدنى من الموارد الحسابية**.**