Detecting Road Tunnel-Like Environments using Acoustic Classification for Sensor Fusion with Radar systems

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Abstract. Radar systems equipped with Misalignment Monitoring and Adjustment (MM&A) face challenges in accurately functioning within complex environments, particularly tunnels. Standard radar system design assumes constant background activity of the MM&A throughout a host vehicle's ignition cycle, monitoring for misaligned radar sensors and mitigating issues associated with faulty radar measurements. However, the presence of tunnels and other unfavorable driving conditions can influence MM&A, thereby affecting its performance.
To address this issue, it is crucial to develop a reliable method for detecting tunnel-like environments and appropriately adjusting the MM&A system. This research paper focuses on the novel acoustic sensing system called SONETE (Sonic Sensing for Tunnel Environment) for classification of acoustic signatures recorded by pressure zone microphone to accurately identify tunnel environments.
The study aims to explore acoustic features and classification algorithms to distinguish between road and tunnel environment and using a sensor fusion with radar systems, suspend the MM&A system accordingly. By tackling this problem, the research contributes to the advancement of intelligent transportation systems by enhancing radar technology's robustness in complex environments and ensuring effective MM&A adjustments in tunnels.
Overall, this paper demonstrates the potential of using acoustic signatures as a complementary sensor for tunnel detection in vehicles where traditional sensors have limitations.

Keywords: Misalignment monitoring and adjustment · Acoustic signatures · Classification · Tunnel detection.

1 Introduction

The presence of tunnel like environments might affect Advanced Driver Assistance Systems (ADAS). In this study we are focusing on radar systems. One of the features in radar systems is MM&A, which performs a process of assessing and correcting the alignment of radar components to ensure optimal system performance. Signal reflections in tunnel like environments can result in overlapping or delayed signals reaching the radar system, leading to inaccuracies in target detection and localization. Misalignment in such scenarios can amplify the effects of signal reflections, making it challenging to distinguish between direct and reflected signals.

In this study we are exploring use of a complementary sensor for tunnel detection in order to compensate MM&A challenges in tunnel like environments. We will explore acoustic phenomena of the sudden change in an acoustic environment. In order to achieve this, an externally mounted acoustic pressure sensor proves to be suitable. Selected sensor configuration should remain unaffected by the tunnel's geometry, including wall curvature and internal infrastructure such as Heating, ventilation, and air conditioning (HVAC) systems and piping.

The driver, when listening to the aural landscape before and after the tunnel, may not be consciously aware of the tunnel's size or any specific internal characteristics. However, the presence of a tunnel is clearly perceivable throughout its entire length, with the driver's reaction time (i.e., resolution) determined by the capabilities of the human auditory system.

2 Related studies

Numerous research studies have extensively explored different approaches and technologies for vehicle localization and tunnel detection. For instance, using LiDAR sensors and imaging technologies mounted on vehicles to acquire the geometry and structural information of tunnels while the vehicle is in moving [23, 24, 27].

Acoustic and vibration signals have also been effectively utilized for tunnel detection. Studies have examined the use of microphones to capture these signals and analyzed their distinct patterns or characteristics [13, 28].

Radar sensors integrated in vehicles could be used for tunnel detection by detecting changes in signal reflections. Researchers have explored diverse radar-based techniques, including Doppler radar, in order to assess their potential for tunnel detection [17, 25, 21].

Moreover, imaging systems have been deployed for tunnel detection, leveraging their capabilities to identify tunnel-like environments [1]. Certain research has focused on utilizing the object elevation property and applying Gaussian filtering techniques for detecting tunnel environments [7].

These comprehensive research studies highlight the diverse range of techniques and technologies being explored in the field of tunnel detection, effectively demonstrating the advancements made in this domain.

2.1 Discussion of related studies

This article shows use of pressure zone microphone (PZM) for tunnel detection through acoustic signature analysis, and offers some distinct differences compared to the previously mentioned detection methods.

Acoustic pressure variations are accurately captured by pressure zone microphones, which exhibit high sensitivity and can detect even subtle changes in sound pressure levels. On the other hand, LiDAR, imaging technologies, and radar sensors utilize different sensing modalities such as light, electromagnetic waves, or radio waves.

When it comes to tunnel environments, pressure zone microphones are primarily employed to analyze their acoustic signatures or characteristics. This analysis involves examining the frequency content, amplitude, and temporal patterns of sound signals collected by these microphones. In contrast, LiDAR, imaging technologies, and radar sensors focus on capturing the geometric or structural information of tunnels, rather than directly studying their acoustic properties. One notable advantage of pressure zone microphones is their ability to provide real-time monitoring of the acoustic environment while a vehicle is in motion. This allows for continuous detection and characterization of tunnel-like environments. Conversely, other detection methods often require periodic measurements or snapshots of the environment.

It's important to note that pressure zone microphones can be sensitive to internal infrastructure elements present in tunnels, such as HVAC systems or piping. These internal components may introduce additional noise or interfere with the analysis of acoustic signatures. Therefore, the implementation of noise filtering algorithms or physical isolation methods becomes necessary to minimize the unwanted effects caused by the internal infrastructure. In contrast, other detection methods like LiDAR or radar are generally less affected by these internal infrastructure elements.

Another advantage of pressure zone microphones is relatively low cost compared to specialized LiDAR or radar systems. They are also relatively easy to install and integrate into existing vehicles or monitoring systems, making them a cost-effective option for tunnel detection through the analysis of acoustic signatures.

3 Methodology

3.1 Selected pressure zone microphone

Surface-mounted pressure microphone 147AX [6] was used as it is optimized for testing in the automotive industry. It combines the high precision and stability of a laboratory microphone with a high level of ruggedness, including the ability to function properly in the most challenging environment with vibrations, oil mists, water spray and dirt and dust - and high temperatures up to 125°C. Microphone design and other internal parts makes it resilient to shock and vibrations. It functions well under conditions with vibrations and g-forces from uneven road surfaces and other sudden directional shifts as encountered in real-life driving tests.

Table 1. 147AX Specifications

Specification	Value
Frequency range (±1 dB)	5 to 12.5 kHz
Frequency range (±2 dB)	3.15 to 20 kHz
Dynamic range lower limit	19 dB(A)
Dynamic range upper limit	133 dB
Set sensitivity @ 250 Hz (±2 dB)	42 mV/Pa
Set sensitivity @ 250 Hz (±2 dB)	-27 dB re 1V/Pa
Output impedance	$< 50\Omega$
Static pressure coefficient @250 Hz, typical	-0.02 dB/kPa

The provided Table 1 contains specifications of the pressure microphone suitable for tunnel detection.

The microphone has a wide frequency range from 5 kHz to 12.5 kHz (±1 dB) and 3.15 kHz to 20 kHz (±2 dB). Tunnels often exhibit specific acoustic characteristics within certain frequency ranges. By capturing and analyzing the acoustic signals within these ranges, the microphone can detect and differentiate tunnel environments from other surroundings.

Tunnels can have varying levels of ambient noise or signal strength. The microphone has a high dynamic range, with a lower limit of 19 dB(A) and an upper limit of 133 dB. This wide dynamic range allows the microphone to capture both low-level ambient sounds and high-intensity sounds within the tunnel environment.

Sensitivity level at 250 Hz is 42 mV/P which is important for detecting the acoustic signatures specific to tunnels, which may have characteristic frequencies and amplitudes. The microphone's sensitivity enables it to capture and analyze these signals effectively.

Output impedance of less than 50 Ohms ensures that the microphone can provide a strong and stable output signal, allowing for accurate and reliable measurements of the acoustic environment.

Static pressure coefficient of -0.02 dB/kPa at 250 Hz indicates its ability to maintain consistent performance even in the presence of static pressure variations. This is important in tunnel environments, where air pressure may change due to factors such as ventilation or vehicle movement.

3.2 Recording audio signals

Microphone was placed on the vehicle (Škoda Karoq) at two positions. First position was on the right side of the vehicle where microphone was exposed to wind, and second position below back door handle making microphone less

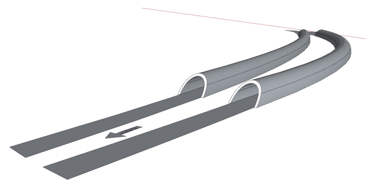

Fig. 1. Mišeluk tunnel model.

exposed to wind, see Figure 5. Recordings of audio signals were done in Mišeluk tunnel, Novi Sad, Serbia showed in Figure 1.

Recordings were made in two sessions, respectively to microphone positions, using a portable multi-channel sound analyzer Voyager at sample rate of 48 KHz [12]. Vehicle speed was in range between 70Km/h and 80Km/h. One set of recordings were in a quiet environment without traffic, and other in a quite busy environment with other vehicles on the road.

Audio samples were cut into 1 second length to be used in the signal processing algorithms showed in Figure 5.

3.3 Time-frequency spectrum analysis

The approach we used to identify tunnel-like environments is through the analysis of the time-frequency spectrum of acoustic signals. In our preliminary experiments, we determined that the presence of a dominant frequency component at around 1 kHz reliably indicates the presence of a tunnel-like environment.

We analyzed time-frequency spectrum to check the distribution of energy in the frequency domain over time, see Figure 2. By capturing the variations in the spectral content of the acoustic signals, analysis revealed specific patterns and features associated with tunnel environments. When a vehicle enters a tunnel, analysis showed that there is a noticeable shift in the time-frequency spectrum of the acoustic signal. The sudden change in the acoustic environment shows a distinct shift in the energy distribution across different frequency bands. In particular, the presence of a dominant frequency component at around 1 kHz becomes more noticeable when entering a tunnel, see Figure 2. This frequency component can be attributed to the interaction between the vehicle's motion and the tunnel's geometry, resulting in specific resonances or reflections that are characteristic of tunnel-like environments.

In Figure 2 we see a dominant frequency component at around 1 kHz. This was used as a reliable indicator of tunnel presence. Algorithms and techniques can be developed to automatically detect and analyze the sudden changes in the time-frequency spectrum, allowing for real-time identification of tunnel-like environments. By focusing on the distinctive features of tunnel environments, such as the dominant frequency component at around 1 kHz, the research aims to develop accurate method for tunnel detection based on the analysis of the time-frequency spectrum of acoustic signals.

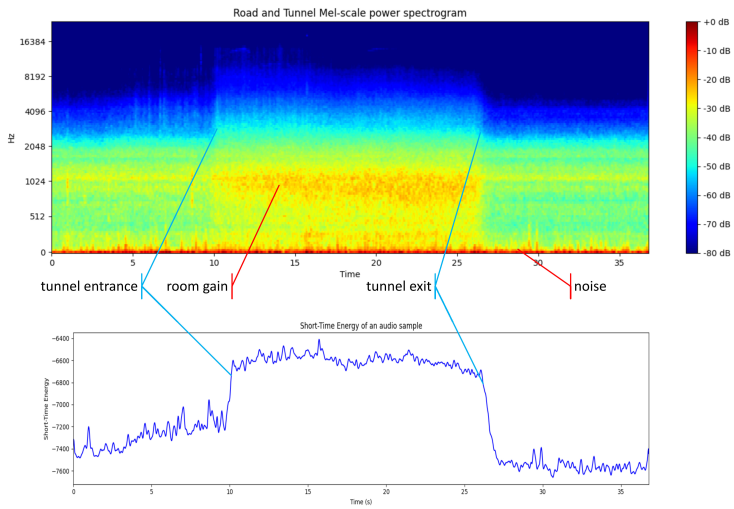

Fig. 2. Mel-scale power spectrogram and Short-Time Energy of raw audio sample.

3.4 External influences

Handling of external influences are crucial factors in designing an effective detection system for tunnel environments. One important aspect considered was the selection of an appropriate frequency range used. In the case of road and tunnel detection, it has been determined that the relevant frequency range for capturing the acoustic signatures is from 500 Hz to 2 kHz, see Figure 6.

By focusing on this frequency range, the system can effectively capture and analyze the specific acoustic characteristics associated with roads and tunnels. These frequencies are known to contain vital information related to the road and tunnel environment, such as reverberations, echoes, and specific resonance patterns.

To ensure accurate detection, frequencies outside of the relevant range were filtered out. Filtering out frequencies above and below the desired range helps to eliminate unwanted noise and interference that may arise from external sources, such as road traffic, wind, or other environmental factors.

3.5 Data collection process

The audio processing pipeline for tunnel detection involved several steps. First, audio samples with a duration of 1 second were re-sampled from the original 48 kHz to 8 kHz, which had been found to yield good results, and also filter some noise out.

Next, Mel-frequency spectrograms (MELs) were computed from the re-sampled audio samples. The MEL spectrograms represented the spectral energy distribution of the audio signals across different frequency bands.

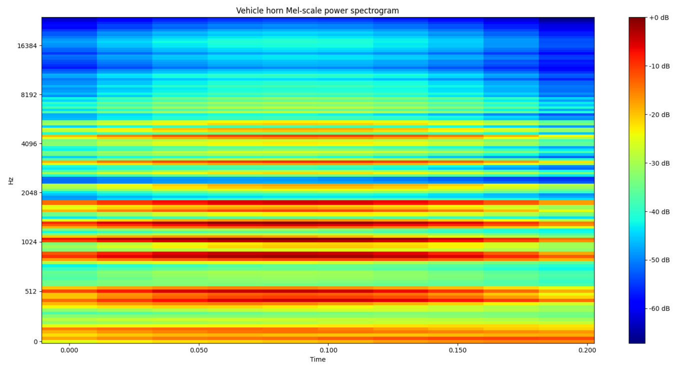

Fig. 3. Vehicle horn spectrogram.

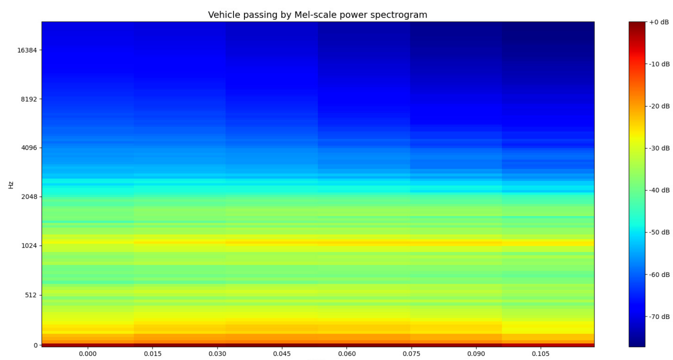

Fig. 4. Vehicle passing by spectrogram.

After generating the MEL spectrograms, a filtering operation was applied to isolate the frequency range of interest. The aim was to focus the analysis on the relevant frequency components. Specifically, the MEL coefficients outside the range of 500 Hz to 2 kHz were filtered out, see Figure 6.

Once the filtering was completed, the resulting filtered MEL spectrograms served as the basis for extracting features using the Mel-frequency cepstral coefficients (MFCCs) technique. The MFCCs are calculated by taking the discrete cosine transform (DCT) of the logarithm of the filtered MEL spectrograms.

These steps were performed using the Python programming language [16], which provided a versatile and efficient environment for audio data processing.

Several Python libraries were used to streamline the various steps. The scikit-learn library [14] played a crucial role in providing powerful tools for data preprocessing, feature extraction, and machine learning algorithms.

The scipy library [20] proved invaluable for its comprehensive suite of signal processing functions. These functions were utilized for tasks such as Fourier transforms, filtering operations.

A key component of the data collection process was the utilization of the librosa library [11], which is specifically designed for audio and music signal analysis. Librosa provided a high-level interface and a wealth of functionality tailored for tasks such as audio loading, resampling, spectrogram computation, and feature extraction. Resulting data was shown via matplotlib library [8].

By following this pipeline, the system was able to preprocess the audio samples, extracting MFCC features from the filtered MEL spectrograms within the relevant frequency range of 500 Hz to 2 kHz, see Figure 6 and Figure 7. These MFCC features served as valuable inputs for subsequent analysis, classification, and detection algorithms, enabling the system to effectively differentiate tunnel-like environments based on their acoustic signatures.

These below formulas describe the mathematical operations involved in computing the MEL spectrogram and extracting the MFCC features:

- Computing the MEL Spectrogram:
  - Apply the Short-Time Fourier Transform (STFT) to audio signal $x(t)$: $X(n,\omega) = \sum_{m=0}^{N-1} x(m) \cdot w(m-n) \cdot e^{-j\omega m}$
    (This is a simplified equation which assumes that the audio signal is zero outside the range of 0 to $N-1$, where N is the length of the window. This is a frame-based approach, where the signal is divided into frames of fixed length.)
  - Compute the magnitude spectrum $|X(n,\omega)|$.
  - Apply a Mel filterbank to the magnitude spectrum: $S(m,t) = \sum_{\omega=0}^{N/2} H(m,\omega) \cdot |X(n,\omega)|^2$
  - Apply a logarithmic compression to the MEL spectrogram: $S(m,t) = \log(1 + S(m,t))$
- Extracting MFCC Features:
  - Apply the Discrete Cosine Transform (DCT) $S(m,t)$: $Y(p,t) = \sum_{m=0}^{M-1} C(m,t) \cdot \cos\left(\frac{\pi}{M}(m+0.5)p\right)$
    (The equation calculates each MFCC coefficient $Y(p,t)$ by summing the product of the Mel-scaled filterbank energies or log-compressed spectrogram coefficients $C(m,t)$ and the cosine of a specific argument $\frac{\pi}{M}(m+0.5)p$. The index m iterates over the filterbank or spectrogram coefficients, and M represents the total number of filters or coefficients.)
  - Select a subset of the resulting DCT coefficients $Y(p,t)$ to represent the MFCC features.

4 Analysis and Results

In this section, we present the results of our study on road and tunnel acoustic signature classification combined with Principal Component Analysis (PCA). We begin by providing a detailed analysis of the obtained data, followed by a discussion of the implications and reliability of our findings.

The dataset used for this study consisted of audio spectrograms extracted from road and tunnel environments. Each spectrogram was processed to extract

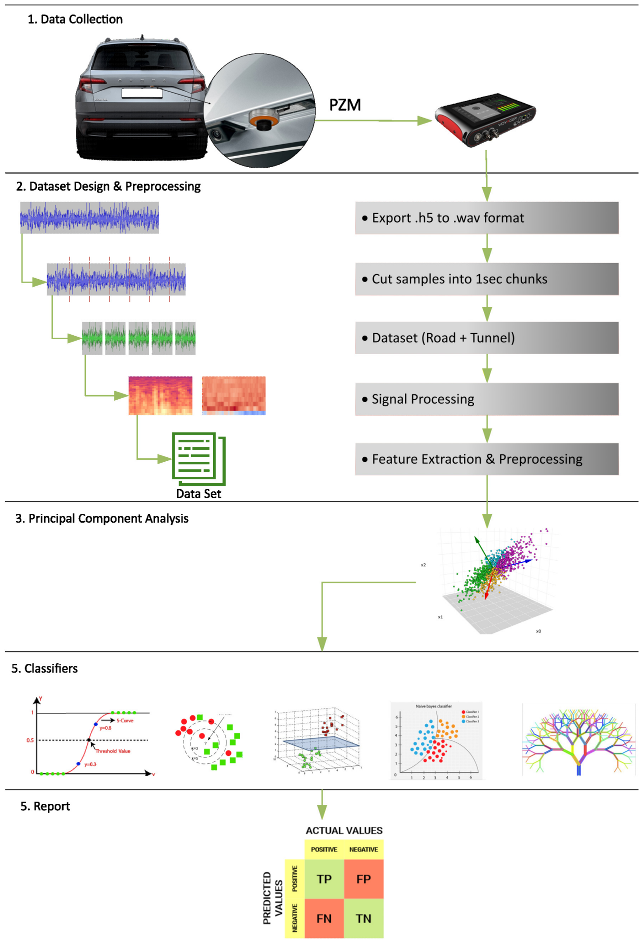

Fig. 5. Audio signal classification process. [19, 10, 22, 26, 9, 4, 2, 3, 6, 12]

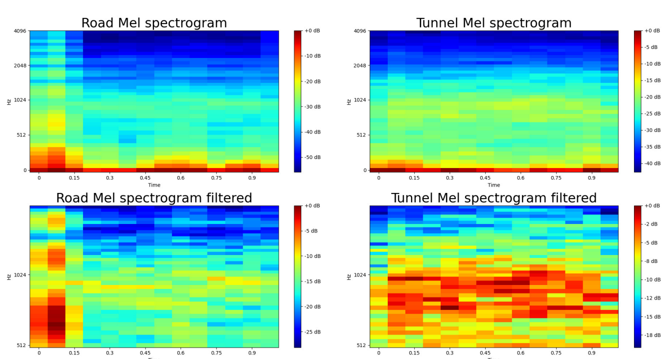

Fig. 6. Mel spectrogram for road and tunnel.

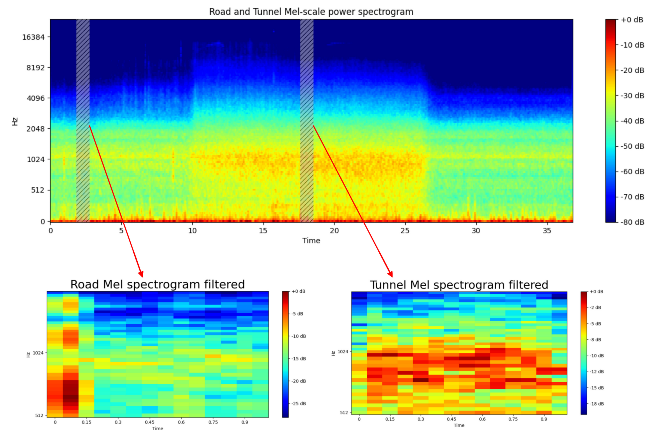

Fig. 7. Signals for classification.

relevant features, and PCA was applied to reduce the dimension of the data. The resulting principal components represented the most informative aspects of the audio signals Figure 5. A total of 280 samples were available, with 200 samples allocated for training and 80 samples reserved for testing the performance of the classification models.

Firstly, the data was scaled using the RobustScaler, which helps normalize the features and make them less sensitive to outliers. This step was crucial to ensure that all features have a similar scale and avoid biasing the classification models.

4.1 Principal Component Analysis

After scaling, PCA (Figure 9) was applied to reduce the dimensionality of the feature space. PCA, short for Principal Component Analysis, is a widely used dimensionality reduction technique that transforms the data into a new set of uncorrelated variables called principal components [5]. This transformation is achieved by finding linear combinations of the original features that capture the maximum variance in the data. By doing so, PCA helps to extract the most important information while reducing the dimensionality of the dataset.

In the specific case of the PCA accuracy plot (Figure 8), which depicts the performance of PCA for different numbers of components using k-fold cross-validation, an interesting observation can be made. Initially, as the number of components increases, there is a noticeable improvement in the accuracy of the PCA-based model. This suggests that the early principal components capture the essential information that contributes to accurate classification or prediction. However, as the number of components continues to increase, the improvement in accuracy becomes less substantial. Beyond a certain threshold, typically around 50 components in this case, the accuracy curve begins to flatten out, indicating that additional components contribute less significantly to the overall performance. This suggests that a substantial portion of the discriminatory information is captured within the first 50 components, and incorporating more components provides diminishing returns in terms of accuracy improvement.

This finding reinforces the notion that PCA effectively captures the most relevant and informative aspects of the data, allowing for dimensionality reduction without sacrificing much accuracy. By retaining a subset of the most important principal components, we can achieve a compact representation that retains the discriminatory power necessary for accurate classification or prediction tasks.

4.2 Classification

Five different classification models were employed in this study: Logistic Regression, Support Vector Machine with c-support vector classification (SVM/SVC), K-Nearest Neighbors (KNN), Gaussian Naive Bayes (NB), and Random Forest. Each model was trained using the training dataset and evaluated on the test dataset.

The performance of each classification model was assessed using various evaluation metrics, including accuracy, precision, recall, and F1-score. Confusion matrices were also generated to visualize the classification results, see Table 2.

The Logistic Regression model achieved a high accuracy of 98.75% on the test dataset. The precision, recall, and F1-score for both road and tunnel classes were consistently high, indicating reliable classification performance.

The SVM model demonstrated a strong performance with an accuracy of 95.62%. It exhibited balanced precision, recall, and F1-score for both road and tunnel classes, suggesting effective discrimination between the two classes.

The KNN model yielded an accuracy of 70% on the test dataset. While it achieved a high recall for the tunnel class, its precision and F1-score were relatively lower for both road and tunnel classes, indicating some misclassifications.

The Gaussian NB model attained an accuracy of 83.75%. It demonstrated a higher precision and F1-score for the road class compared to the tunnel class. However, its recall for the tunnel class was notably higher, suggesting better identification of tunnel audio samples.

The Random Forest model achieved an accuracy of 80% on the test dataset. It exhibited balanced precision, recall, and F1-score for both road and tunnel classes, indicating reliable classification performance.

4.3 Results overview

The results indicate that both Logistic Regression and SVM models outperformed the KNN, Gaussian NB, and Random Forest models in accurately classifying road and tunnel audio samples. Logistic Regression showed the highest accuracy, precision, recall, and F1-score, indicating its suitability for audio signature classification in road and tunnel environments.

The KNN model exhibited lower accuracy and precision, suggesting its limitations in effectively distinguishing between road and tunnel classes. The Gaussian NB and Random Forest models achieved moderate accuracies, with slightly varying precision, recall, and F1-scores for road and tunnel classes. These models may be suitable for specific applications or when a balanced performance is desired.

Overall, the findings presented suggest that audio signature classification for environments like road and tunnel can be effectively accomplished using Logistic Regression (Figure **??**) or SVM (Figure 10) models. Further research could focus on refining and optimizing these models, as well as exploring additional feature extraction techniques to improve classification performance.

Analysis of PCA component cumulative variance (Figure 9) shows an interesting trend. Initially, as the number of principal components increases, there is a rapid increase in the cumulative variance explained. This indicates that the early components capture the majority of the variability in the data.

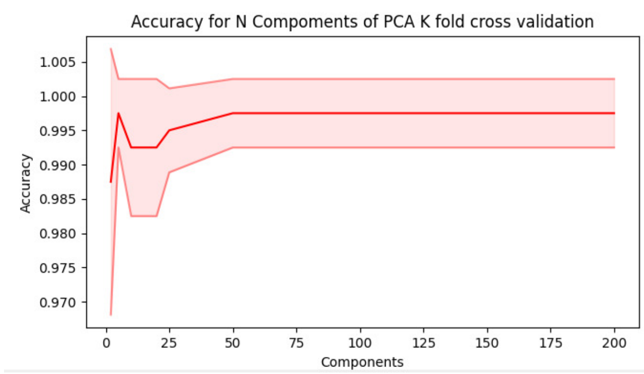

Fig. 8. PCA accuracy for N components.

However, we observed a diminishing rate of increase in the cumulative variance. We reach a point where adding additional components contributes only marginally to the cumulative variance explained. In fact, beyond a certain threshold, as shown in Figure 9, the curve becomes nearly linear.

This suggests that a significant amount of information of the data is captured by a relatively small number of principal components. These components represent the most dominant and essential features that characterize the acoustic signatures of tunnel environments. As we incorporate more components beyond this critical threshold, the additional information gained becomes increasingly marginal.

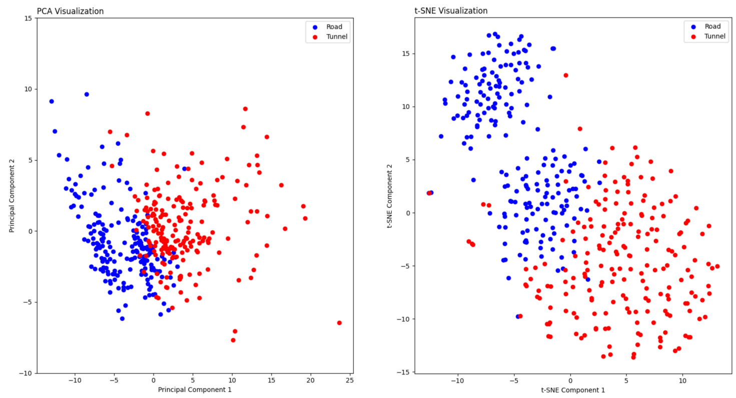

Fig. 9. Principal component analysis.

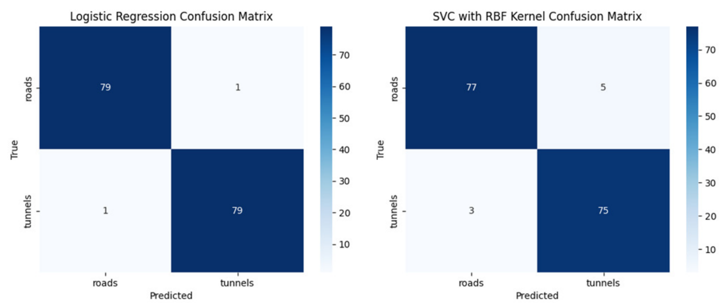

Fig. 10. Confusion matrix of Logistic Regression and SVM.

5 Misalignment Monitoring and Adjustment for Radar Systems

Monitoring and adjusting the alignment of radar systems is a critical process aimed at optimizing their performance. Radar systems consist of various hardware components, such as antennas, transmitters, receivers, and signal processing modules, all of which need to be properly aligned for accurate and reliable operation.

Misalignment in radar systems can result from mechanical vibrations, environmental conditions, installation errors, or component degradation over time. These misalignments can have detrimental effects on system performance, including reduced detection range, inaccurate target localization, degraded signal quality, and increased false alarms.

Hence, it is essential to assess and correct misalignment in radar systems to ensure their effectiveness. This can be achieved through various techniques, such as sensor-based measurements, optical alignment systems, or signal analysis methods. These techniques enable operators or automated systems to analyze

Table 2. Model evaluation.

Sample	Model	Accuracy	Inference time
1 sec	LogisticRegression	98.75%	$\sim$ 1 ms
	SVC	95.625%	$\sim$ 15.6 ms
	GaussianNB	83.75%	$\sim$ 1 ms
	RandomForest	80%	$\sim$ 3 ms
	K-Nearest Neighbors	70%	$\sim$ 130.9 ms
0.5 sec	LogisticRegression	97.5%	$\sim$ 1 ms
	SVC	93.7%	$\sim$ 10.6 ms
	GaussianNB	86.8%	$\sim$ 1 ms
	RandomForest	81.8%	$\sim$ 2 ms
	K-Nearest Neighbors	73.1%	$\sim$ 80.9 ms
0.1 sec	LogisticRegression	94.3%	$\sim$ 1 ms
	SVC	88.1%	$\sim$ 5.6 ms
	GaussianNB	61.8%	$\sim$ 1 ms
	RandomForest	76.8%	$\sim$ 3 ms
	K-Nearest Neighbors	76.2.1%	$\sim$ 12.9 ms

and identify the presence and extent of misalignment. The ultimate goal of this monitoring and adjustment process is to secure maximum accuracy, sensitivity, and reliability in radar system operations.

By employing rigorous analysis and assessment, radar system misalignment can be properly diagnosed and addressed. Findings from such analysis allow for informed conclusions and the development of effective alignment strategies. This comprehensive approach guarantees that radar systems operate at their highest potential, enabling them to fulfill their intended functions with optimal performance.

5.1 Environment impact

When a vehicle is traveling trough a tunnel, several factors come into play that can affect the alignment and performance of radar systems such are: signal reflections and attenuation, electromagnetic interference etc.

Tunnels are enclosed environments with reflective surfaces, such as walls and ceilings, which can cause signal reflections and multi-path propagation. These reflections can result in overlapping or delayed signals reaching the radar system, leading to inaccuracies in target detection and localization. Misalignment in such scenarios can amplify the effects of signal reflections, making it challenging to distinguish between direct and reflected signals.

The presence of walls and other structures in tunnels can cause signal attenuation, leading to a decrease in signal strength. This attenuation can reduce the effective range and sensitivity of the radar system, making it more difficult to detect and track targets accurately.

Tunnels often have electrical infrastructure, such as lighting, ventilation systems, and power cables, which can generate electromagnetic interference (EMI).

EMI can introduce noise and distortions into the radar signals, affecting the quality and reliability of the measurements.

5.2 Mitigate issues of misalignment in tunnel environments

One of the mitigation of issues with misalignment of radar systems in tunnel like environments, is to provide information of environment to the system in order to incorporate environmental compensation techniques. The radar system can adapt to the specific conditions inside the tunnel, compensating for signal loss and addressing the challenges posed by signal reflections and multipath propagation. This can help improve the quality of radar measurements and mitigate the impact of misalignment-induced errors.

We propose in this paper novel acoustic system called SONETE [18] (Sonic Sensing for Tunnel Environment) for automotive diagnostics.

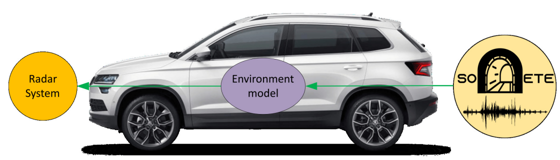

Fig. 11. Sonete system. [15]

Assistance and driving functions, for example, lane keeping or automated driving, require information about the static and dynamic environment of a vehicle. Usually this information is available trough a sensor data fusion, where information about different environments is available. Here we add SONETE (Figure 11) as a complementary sensor to a data fusion to ensure that information about vehicle tunnel entrance is available, thus using sensor data fusion to create a comprehensive view of the vehicle's surrounding.

Utilizing information of tunnel presence, Figure 12, radar system can switch off MM&A feature while the vehicle is traversing trough the tunnel, thus not degrading performance of the system when vehicle exits the tunnel.

5.3 Limitations

The presented solution of using PZMs for tunnel detection through acoustic signature analysis has provided valuable insights and plausibility. However, it is important to acknowledge several limitations that should be taken into consideration when interpreting the results and guiding future research.

We analyzed acoustic signatures of a specific tunnel "Mišeluk", and in order to enhance the robustness of the SONETE system, it is crucial to gather

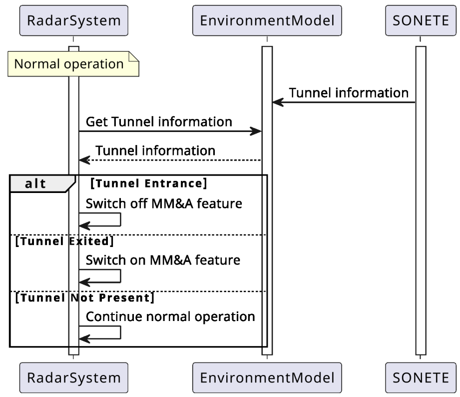

Fig. 12. Mitigate issues of MM&A in tunnel environments.

recordings from more tunnels with varying characteristics. This would involve considering tunnels of different sizes, materials, traffic conditions, and geographical locations. With this, proposed approach can be better evaluated and its applicability to a wider range of tunnel environments can be assessed.

Placement of the PZM we believe can impact the overall system performance and classification. Optimal placement of the PZM might vary depending on factors such as the vehicle type. Therefore, further investigations will be needeed to explore the effects of different PZM placements to determine the most effective and reliable positioning for capturing tunnel acoustic signatures. This would involve systematically evaluating the influence of microphone location and orientation on the accuracy and consistency of the collected audio data.

The analysis and processing of the audio data in this study were performed on a Windows based machine (Windows PC) with Intel I7-11850H and 32GB of RAM memory, using Python and relevant libraries. However, it is crucial to assess the feasibility and performance of the proposed approach on embedded systems or real-time monitoring platforms. Evaluating the algorithm's implementation on resource-constrained devices would provide insights into its practical viability for on-board vehicle systems or embedded monitoring systems.

6 Conclusion

Time-frequency spectrum analysis of road and tunnel audio signals, showed the potential of utilizing acoustic signatures for classification of tunnel like environments, thus implying the use of PZMs for tunnel detection plausible.

In this paper we used information of the environment, gathered from a proposed novel SONETE system, to enhances the robustness of radar technology in complex environments and ensures effective MM&A adjustments in tunnels, where traditional sensors often encounter limitations.

Recordings from other tunnels with varying characteristics should be gathered in order to enhance the robustness of the SONETE system. This would involve considering tunnels of different sizes, materials, traffic conditions, and geographical locations. With this, proposed approach can be better evaluated and its applicability to a wider range of tunnel environments can be assessed.

In conclusion, this research paper highlights the significance of addressing the challenges faced by radar systems equipped with Misalignment Monitoring and Adjustment (MM&A) in complex environments, specifically tunnels.

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