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Assessing Signal Distortion in Seismic Sensor Security Systems: A Machine Learning Approach to Target Identification

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ABSTRACT

Providing security is one of the most critical tasks worldwide, particularly in vast areas (e.g., forests) and the border regions of certain countries. Numerous techniques have been proposed to control these areas by providing security. However, economic and practical obstacles prevent the completion of this task as effectively as possible. Traditional methods include setting up security fences or barbed wire and deploying robots or security personnel. However, these methods are costly and complex. Moreover, they frequently fail to achieve the desired goal, particularly under changing environmental conditions and regional characteristics. Given their sensitivity in tracking targets, low cost, and lightweight, the use of sensors (e.g., seismic sensors) has been one of the most successful methods for providing security. However, obstacles still exist. In this work, an experiment was performed to accurately determine the reasons for the distortion of the signals produced by these sensors. The experimental data were collected under variable conditions and from four different surfaces (asphalt, mud, grass, and soil). An experiment was also conducted with various targets (humans, animals, motorbikes, and cars). Each target performed different activities to accurately and comprehensively understand the signal changes. After that, the signals were processed, and the resulting signals were analyzed in detail, validated, and then classified using two algorithms: k-nearest neighbors (k-NN) and support vector machine (SVM). High accuracies were obtained for k-NN (96.88%) and SVM (98.57%).

1. INTRODUCTION

The ability to effectively detect targets across various domains has gained significant importance in the modern era. This ability is necessary in the military and civilian sectors, which have unique requirements and challenges. The critical nature of target detection has motivated numerous researchers to explore and innovate across a wide range of methods that aim to enhance detection capability, particularly in areas that face various types of illegal intrusions. When armed incursions suddenly occur, significant economic and human catastrophes may result; hence, urgent action is necessary to prevent such incursions from escalating [1]. In addition, unauthorized migrants who frequently gather at the borders of some countries may seize the opportunity to enter these countries in groups, imposing significant economic effects on these countries [2]. Meanwhile, poachers can infiltrate environmental reserves and natural parks, causing considerable harm by hunting and killing endangered animals, especially those on the brink of extinction [3].

Considering the aforementioned challenges, robust research is necessary to create effective security measures for protection and continuous monitoring. Initially, electric fences and electronic balloons have been installed in some areas to provide enhanced security. Furthermore, the integration of different types of cameras in surveillance systems. Within this approach, efforts have focused on improving the processing of pixels, leading to increased efficiency and accurate target discrimination. This capability enables continuous visual monitoring and recording, which are crucial for security and investigation, are realized [4]. In addition, robots equipped with advanced sensors and autonomous navigation systems have been employed to conduct comprehensive investigations in areas considered too dangerous or inaccessible for humans [5]. Regardless of whether they are used independently or with robots, improving the performance of algorithms is also a significant area of focus; this process aims to achieve precise detection of the intended targets in open and closed environments [6].

However, the theories mentioned above and their applications are inherently financially demanding and require substantial data storage capacity. This challenge is particularly significant when these theories and applications are deployed over regions where vast coverage is essential, such as extensive border areas between countries or large military zones. Considering the financial burden and logistical challenges associated with these technologies, many researchers have searched for alternative solutions. Accordingly, different types of sensors have gained popularity because of their low cost and manageable data storage requirements. Among them, vibration or seismic sensors have been proven to be valuable. These sensors have been widely utilized in various security applications because of their ability to detect friction between objects or targets and the ground [7] which produces slight surface distortions. Vibration sensors can accurately detect these distortions by converting them into electrical signals; hence, the presence of objects can be sensed effectively [8]. This capability highlights the effectiveness of vibration sensors in detecting a wide range of targets, including people, vehicles, and animals [9, 10].

Seismic sensors exhibit numerous advantages, such as being cost-effective, requiring minimal operational power, and generating data that are easier to store and manage than conventional monitoring systems. Their cost-effectiveness and energy efficiency make them particularly suitable for large-scale deployments. In addition, the sensors' capacity to produce manageable datasets simplifies the processing and analysis of collected information. This feature further enhances the practicality of these sensors. Furthermore, vibration sensors can be buried discreetly under the soil, providing a significant advantage for concealment. Such hidden deployment helps avoid detection by targets and ensures that sensors are protected from environmental factors and tampering. The use of sensors in various security scenarios ranging from border monitoring to wildlife conservation emphasizes their importance as practical and effective alternatives in target detection. Given their versatility and efficiency, vibration sensors have become invaluable tools in security and surveillance. The deployment of these sensors across diverse environments and their ability to reliably detect targets highlight their crucial role in modern detection systems [11].

Despite their advantages, the use of signal-based detection methods also poses some challenges. Firstly, the signals generated by seismic sensors can be influenced by various factors, complicating their deployment and effectiveness. The localization of sensors is a significant concern because they are frequently used in diverse areas, such as forests, urban environments with large buildings, or other complex terrain. Some regions may not be fully covered, leading to gaps in detection if sensors are not placed optimally or if the mapping of targeted protected areas is inadequate [12]. The characteristics of the environment in which these sensors will be placed are also critical in determining the speed and amplitude of the waves that will be detected. For example, the characteristics of the ground surface, i.e., whether it is flexible or rigid, significantly affect wave amplitude. A rigid surface may reflect waves differently than a flexible one, affecting the accuracy of the detected signals. Given such variability, understanding how different surfaces influence signal propagation is essential to ensure reliable detection [13, 14]. In addition, the activity of the target plays a significant role in the characteristics of the signals. For example, vehicle load, wheel type, and the extent of the target's friction with the ground surface contribute to the resulting distortions regardless of whether the target is human or vehicle. Subsequently, these distortions are converted into electrical signals; however, the characteristics of these signals can vary widely depending on the aforementioned factors [10, 14].

Another critical factor that affects the accuracy of signals generated by seismic sensors is environmental noise. Proximity to factories, train tracks, aircraft runways, or other sources of constant noise can interfere with the ability of sensors to detect targets accurately. In the study by Parihar et al. [15], where elephant noise was problematic, the researchers had to use a low-pass passive RC filter with a cutoff of 110 Hz to eliminate the sounds of elephants, thereby improving the accuracy of the signal. The above factors can result in potential inaccuracies in detection results, including false positives or false negatives. Therefore, studying and understanding the behavior of these signals and the external factors that can affect them is crucial. This research area has become increasingly important, and numerous studies have focused on mitigating environmental noise and optimizing sensor deployment strategies to reduce interference and increase detection accuracy. However, previous research has not fully addressed the practical aspects of understanding signal behavior in certain key areas. To fill this gap, our study aimed to thoroughly investigate the behavior of different types of targets and their interactions with various environments. To achieve this objective, we conducted experiments involving various targets, including humans, animals, cars, and motorbikes, to achieve this objective. Each target demonstrated different activities and behaviors.

In our experiments, we observed humans and animals while running and walking states. For humans, we analyzed the distinct signal patterns generated during brisk running compared with those produced during steady walking. Similarly, we studied moving animals and noted variations in signals produced by different gaits and speeds. Moreover, we tested cars and motorbikes at speeds ranging from slow movement to rapid acceleration as they approached and entered restricted areas. This set of activities enabled us to capture a broad spectrum of signal behavior associated with different types of movement. We conducted experiments in environments with varying surface types to understand how different types of terrain affect signal amplitude. We selected surfaces, such as mud, asphalt, grass, and soil, to represent various real-world conditions. We observed how soft and pliable surfaces affected the amplitude and speed of signals by conducting experiments in muddy areas.

Meanwhile, experiments performed on asphalt provided insights into the influence of hard and rigid surfaces on signal reflection and transmission. Moreover, grass and soil surfaces provided additional variations, highlighting the effects of vegetation and lose ground on signal behavior. By focusing on diverse target activities and environmental conditions, we expect that the presence and movement of the targets will directly affect the signals detected by sensors. Understanding these effects is crucial for improving the accuracy and reliability of detection systems. For example, friction is produced by different types of movement on various surfaces, generating distinct signal patterns that can be used to differentiate among targets.

Furthermore, we investigated the specific characteristics of different environments, such as urban, rural, or natural reserves, which require protection. These environments pose unique challenges and are likely to produce significant variations in sensor signals.

By thoroughly analyzing and examining signals, we aim to increase our understanding of key factors that influence signal generation and propagation. Our goal is to comprehensively understand how different targets and environmental conditions affect signal behavior.

Accurate classification of various target movements will enable us to improve the deployment and effectiveness of vibration sensors in diverse scenarios. This comprehensive analysis will help identify optimal sensor placement strategies and refine signal processing techniques to minimize false positives and negatives.

In summary, our study aims to provide a comprehensive understanding of the interactions between targets and their environments. By addressing these practical issues, we intend to develop robust and reliable detection systems that can be used effectively in various applications ranging from border security to wildlife conservation. In this work, we extensively discuss the points above to elucidate key factors that influence the signals generated by vibration sensors in real-time and during actual events. Our objective is to improve the practical applications of these sensors in target detection by ensuring their reliable and accurate performance across diverse scenarios. We endeavor to improve our understanding and classification of target movements by investigating the behavior of various targets and the effect of different environments on signal propagation. This comprehensive approach will enable us to refine sensor deployment strategies and signal processing techniques, ultimately minimizing false negatives and ensuring the effectiveness of vibration sensors in real-world settings.

1.1 Contribution for paper

This paper makes several key contributions to address the existing gaps in seismic sensor research. While prior studies have explored various sensor types, target detection methods, and environmental conditions, they have often overlooked the simultaneous effects of multiple environmental and target factors on signal behavior. Our research offers a more comprehensive analysis by focusing on the critical factors that influence signal variation: the target type, the target's activity, and the surface on which the target moves.

We propose a novel experimental setup that includes the deployment of eight vertical SM-24 geophones across different surface types, representing both urban and rural environments. This approach enables us to capture the diversity of signal behavior caused by the variation in surface flexibility and hardness, which directly impact wave propagation. Using a range of targets—including humans, animals, motorbikes, and cars—we ensure that the collected data reflects real-world scenarios in which these targets interact with the environment in diverse ways.

Additionally, our month-long data collection period offers a more dynamic perspective on how changes in surface conditions over time due to weather or other environmental factors can affect seismic sensor signals. This extended timeframe allowed us to account for seasonal shifts, ensuring our analysis is robust and applicable across different conditions.

Our key contributions can be summarized as follows:

(1) A comprehensive study of seismic sensor signal variation across multiple surface types and target activities, examining the influence of target behaviors (e.g., walking, running, and moving at different speeds) on the characteristics and morphology of the seismic waveforms generated upon reaching a restricted area.

(2) Deployment of eight vertical SM-24 geophones for real-time data collection under diverse conditions.

(3) Examination of the impact of environmental conditions on seismic signal shape during propagation, identifying and characterizing various conditions (e.g., asphalt, grass, muddy, and soil areas) and how they affect signal characteristics.

(4) Extended monthly data collection to factor in environmental and temporal changes affecting signal behavior.

(5) We employed machine learning for target classification to distinguish between different types of targets based on their seismic signals. These models demonstrated high accuracy in recognizing various targets and activities, underscoring the effectiveness of data-driven approaches for enhancing detection and classification in diverse environments.

The paper is structured as follows: Section 2 reviews related work on seismic sensor target detection. Section 3 details the experimental setup, including signal processing and classification. Section 4 presents results and analysis, while Section 5 provides a discussion. Section 6 concludes with key findings.

2. RELATED WORK

Given the above, using traditional methods to protect restricted areas, city boundaries, or military zones has been proven costly and potentially ineffective because of environmental and climatic changes affecting the investigation of suspicious targets. These methods include deploying personnel (e.g., soldiers, security guards) and installing barbed wire fences, concrete walls, and different types of cameras. This situation has driven researchers to focus on developing advanced technologies that can meet the needs of these areas more efficiently and at a lower cost. One promising solution is the use of seismic sensors. These sensors offer numerous advantages, such as high sensitivity, low power consumption, lightweight, and other benefits, as discussed previously.

The localization of moving military vehicles plays a critical role in border security and protecting high-security facilities. Traditional trilateration equations often face challenges in dynamic environments, leading researchers to propose more advanced methodologies. For instance, Köse et al. [16] address this limitation by introducing a ConvLSTM (Convolutional Long Short-Term Memory) network. This approach captures spatio-temporal features from seismic frequency domain data, integrating Convolutional and LSTM layers into a unified framework. The model processes seismic signals and sensor locations, producing target positions relative to clustered sensors. Using the SITEX02 dataset, the authors demonstrate the effectiveness of clustering and localization with just three sensor nodes. They build on circular trilateration techniques, employing methods such as Angle of Arrival (AOA), Time of Arrival (TOA), Time Difference of Arrival (TDOA), and Received Signal Strength Indicator (RSSI) to estimate target locations accurately.

In structural health monitoring (SHM), innovative and cost-effective data acquisition systems have emerged. For instance, Özdemir et al. [17] have proposed the CEDAS_acc and CEDAS_geo systems, which integrate MEMS (Microelectromechanical Systems) accelerometers and geophone sensors with Raspberry Pi mini-computers. These standalone systems, validated through rigorous tests such as offset tests, frequency response tests and noise tests, demonstrated high accuracy and reliability comparable to commercial sensors. The researchers also developed tools like the RECANA web application to facilitate efficient data processing and analysis, making advanced SHM technologies more accessible and applicable in diverse fields such a seismic monitoring, structural health, and early warning systems.

Moreover, integrating photonic technologies for environmental monitoring has shown promising results in several fields, including high-precision agriculture, landslide early warning, and seismic sensing. Breglio et al. [18] developed advanced seismic and optical fiber sensors for both terrestrial and underwater environments, employing technologies like Fiber Bragg Grating (FBG) and Long Period Grating (LPG) sensors. These optical solutions are compact, provide rich data, and are adaptable to specific environmental needs. However, challenges such as cross-sensitivity and fiber breaks persist. Nonetheless, these innovations have spurred the creation of spin-off companies and the establishment of research centers, with future research focusing on expanding these technologies into safety applications and enhancing their performance with advanced materials and nanotechnology.

Seismic sensors have also proved effective in detecting ground vibrations caused by military vehicles such as tanks. Muda [19] focused on tank-induced vibrations found that while the frequency remains constant at 332 Hz regardless of distance, the amplitude increases as the tank approaches. For example, at 50 meters, the amplitude reached 12.1 volts, whereas at 1000 meters, it was only 4.3 volts. This emphasizes the importance of amplitude analysis over frequency analysis for estimating detection distances. The findings suggest that seismic sensors, when properly deployed, can effectively detect tank movements and provide insights for optimizing sensor placement and network configuration in military and security applications.

To address challenges in low-frequency seismic vibration monitoring, a novel approach [20] using Fiber Bragg Grating (FBG) sensors was proposed. The study introduced an FBG acceleration transducer with a double-curved beam reed pickup structure. The transducer achieved a natural frequency of 41 Hz, with a flat response between 2–32 Hz and a lower frequency limit of 0.5 Hz. It demonstrated high performance with a dynamic range of 76.8 dB and a 966.65 pm/g sensitivity. The compact design, weighing only 200 g, ensures resistance to lateral interference. Further optimizations are underway to enhance its low-frequency capabilities, making it a promising solution for seismic monitoring in environments with low-frequency vibrations.

Recent advances in seismic sensor technology [21] have shown promising applications of low-noise broadband fiber optic sensors in extreme environments such as deep wells, seabeds, and glaciers. The sensors use narrow-linewidth laser frequency scanning and laser interferometric phase interrogation to monitor crustal deformations and earthquakes. The sensors' passive design, temperature resistance, and extended transmission capabilities are particularly beneficial for deep Earth exploration. Researchers are focused on improving noise levels, expanding frequency bands, and developing displacement and velocity sensors. These improvements could further enhance the usability of these systems in harsh environments and address the limitations of traditional seismometers.

According to Sun et al. [22], ground intrusion detection using seismic signals has also seen significant improvements, primarily due to the integration of Variational Mode Decomposition (VMD) and Hilbert Transform (HT). This novel approach decomposes seismic signals into Band-limited Intrinsic Mode Functions (BIMFs) and applies HT to obtain marginal spectra. Based on features such as energy, entropy, and dominant frequency, the classification results achieved an exceptional accuracy of 99.5%. Compared to traditional methods like EEMD-HT and EWT-HT, the VMD-HT method outperformed them in terms of classification accuracy. Researchers aim to enhance the method by addressing mixed signals from multiple intrusion activities, improving both classification accuracy and positioning.

Seismic sensors have also found applications in real-time pavement monitoring systems, such as the study conducted on a French motorway [10]. The system integrates embedded geophones and temperature probes with wireless transmission to monitor pavement deflections, traffic composition, and loads. Over two years of data collection, the system demonstrated high reliability and provided valuable insights for pavement performance analysis. Temperature corrections showed that deflections remained stable, indicating no significant deterioration. Furthermore, the data enabled the identification of heavy vehicle types and load distributions. Comparisons with simulated deflections showed the system's accuracy, particularly for front axles. However, several challenges, such as automating data processing and reducing costs, must be addressed before the system can be widely deployed.

Signal classification has also been explored using deep learning techniques, as demonstrated by Cyriac et al. [9], which utilized a processing and decision-making system (PDS) with a single-axis geophone. The system employed a deep neural network (DNN) to classify signals after digitizing them using an Arduino Mega 2560. In another study, Pucci et al. [23] employed a biaxial seismic sensor system to classify signals generated by activities such as cycling, walking, and running. The Power Spectral Density (PSD) method was used for feature extraction, followed by Principal Component Analysis (PCA) for dimensionality reduction. The classification was performed using Support Vector Machines (SVM) and k-nearest neighbors (k-NN), with a comparative analysis demonstrating their effectiveness for seismic signal classification. These methods were further evaluated using biaxial seismic sensors, with the horizontal sensor detecting signals from cycling and vehicles, while the vertical sensor identified signals from walking and running. The comparative analysis between the SVM and k-NN algorithms highlighted their effectiveness in the classification task.

Other studies, such as those conducted by Ghosh et al. [8] using different types of seismic sensors integrated with analog-to-digital converters (ADC), have explored real-time control with FPGA and processor systems. The tests involved light and heavy vehicles at varying distances and hammer-knocking activities. Signal processing algorithms like Constant False Alarm Rate (CFAR) and Ordered Cell Averaging-CFAR (OCA-CFAR) were employed. These studies indicate the growing importance of real-time control and advanced algorithms in seismic sensor applications.

Finally, seismic sensors have been applied to track animal movements in wildlife monitoring, as demonstrated in studies monitoring elephant activity in forest environments [15]. Data collected from seismic sensors were analyzed using various algorithms, including short-time average/long-time average (STA/LTA), amplitude spectrum of Fourier transform (ASFT), and continuous wavelet transform (CWT). These studies emphasize the versatility of seismic sensors in detecting a wide range of activities, from military and infrastructure applications to environmental and wildlife monitoring.

An extensive experiment [24] conducted at Hunan Normal University in Changsha. Seismic and acoustic sensor data were collected over two weeks, with sensors placed at distances of 15 m for people and 30 m for vehicles. The data were processed for target identification using an evolutionary neural network that combined a genetic algorithm and a neural network. This approach showed promising results for identifying and distinguishing between different target types, offering a novel seismic signal analysis and classification technique.

This research builds upon existing work by introducing a more comprehensive approach to understanding the factors that influence the signals generated by seismic sensors. The preceding experiments revealed that seismic sensors are highly susceptible to external factors that can directly alter the characteristics of seismic waves. A review of recent research in this field, summarized in Table 1, reveals that these studies have not fully addressed the primary factors impacting seismic signals. Consequently, these unaddressed factors can lead to significant changes in the signal, causing false alerts or misclassifications.

The present study identifies three major influences that can alter the shape and characteristics of the outgoing wave: the type of target, its activity, and the surface it interacts with. These influences are critical because they can drastically modify the seismic signal, leading to errors in detection or localization. To address these issues, we focused on analyzing these three key factors considering their impact on signal quality and classification accuracy.

A comprehensive experiment was designed to investigate how these factors influence seismic sensor data. In a farm setting, we utilized eight vertical SM-24 geophone sensors strategically placed on different surfaces (soil, asphalt, grass, and mud). These surfaces were selected to represent a variety of environments—urban, rural, and natural—each with different levels of flexibility and hardness, which directly affect the seismic wave generated by a target. The experiment incorporated four types of targets: human, animal, motorbike, and car. Each target was subjected to various activities to ensure accurate differentiation when entering the test area.

The data collection process lasted a month to account for surface changes over time and to capture variations in target activities across different farm regions. This extended data collection period was crucial to understanding how the generated seismic signals change under different environmental and temporal conditions. By addressing these factors-target type, target activity, and surface conditions-our research provides valuable insights into how seismic sensors can be optimized for more accurate detection and classification, thus reducing false alarms and improving the overall reliability of seismic-based monitoring systems.

This study aims to make significant advancements in the field of seismic sensor technology by offering a deeper and more detailed understanding of the various factors that influence signal quality. These factors, which have often been neglected or insufficiently addressed in previous research, are crucial.

The outcome of this work has the potential to enhance the design and performance of seismic sensor networks, especially in complex environments with dynamic and unpredictable variables.

Table 1. Review of recent research

Authors	Journal	Feature Algorithm	Targets	Activity	Multi-Environment	Area
Köse and Hocaoglu [16]	IEEE Sensors Journal	Convolutional Long Short-Term Memory (ConvLSTM)	Military vehicles	Localization	No	Outdoor
Muda [19]	Journal of World Science	Artificial neural network algorithm	Military vehicles (Tanks)	No	No	Outdoor
Sun et al. [22]	Sensors Journal	SVM	Vehicles, Footsteps, Excavations	No	No	Outdoor
Bahrani et al. [10]	Elsevier	the linear elastic software ALIZE	Traffic vehicles	Pavement deflection, Traffic load monitoring	No	Outdoor
Cyriac et al. [9]	IEEE Sensors Journal	Power spectrum density and SVM, k-NN	Vehicle, Bicycle and human	(bicycle and car) for horizontal,	No	Outdoor
Pucci et al. [23]	IEEE Sensors Journal	Threshold method is referenced by CFAR ordered cell averaging.	Vehicles, Human	No	No	Outdoor
Ghosh et al. [8]	MDPI Journal	Evolving neural network genetic algorithm	Vehicles, Human	No	No	Outdoor
Bin et al. [11]	13thInternational Conf. in IEEE	DNN	Human	No	No	Outdoor
Parihar et al. [15]	Elsevier	STA/LTA, ASFT, CWT	Animal	No	No	Outdoor
Proposed Model		k-NN, SVM	Human, Animal, car and motorbike	Human and animal (run, walk), Car (20 km/h,10 km/h), Motorbike (10 km/h, 5 km/h)	Grass, Soil, Asphalt and muddy	Outdoor

3. METHOD

In this work, we thoroughly investigated factors that influence the signals produced by seismic sensors. We focused specifically on the target type, target activity, and the surface on which the target moves. We recognized the importance of these variables; therefore, we designed a comprehensive experiment that could fully capture their effects on the generated waveforms. Our methodology involved deploying eight vertical SM-24 geophone sensors across different surface types, namely, soil, asphalt, grass, and mud, within a farm environment to simulate urban, rural, and natural conditions. We selected various targets, including humans, animals, motorcycles, and vehicles. Each target was engaged in multiple activities to ensure a robust dataset.

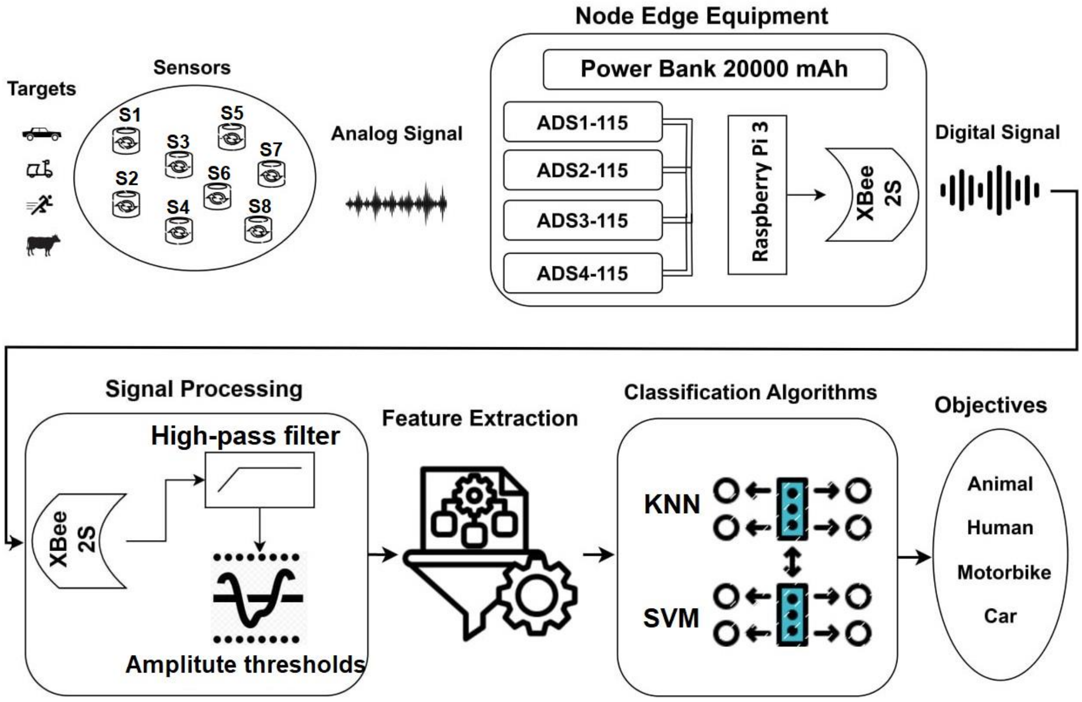


Figure 1. Method used in this study

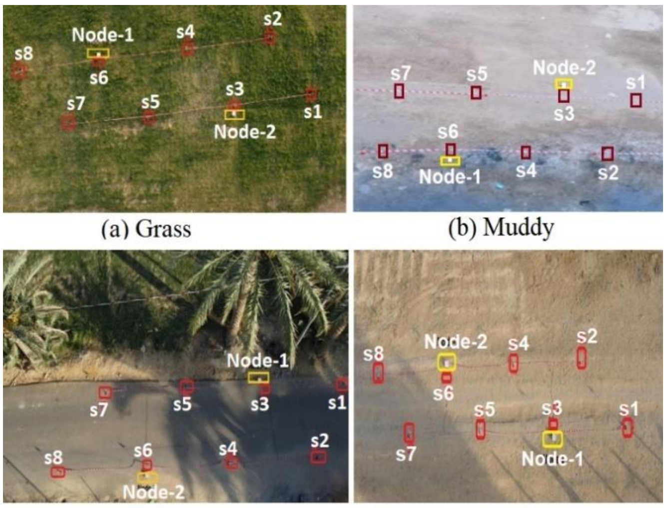
We continuously collected data over a month to enable us to account for temporal variations and environmental changes. In this manner, we could comprehensively understand how various factors affect seismic signals. Apart from data collection, we also focused on signal processing and feature extraction in the time domain to analyze the recorded waveforms. We aimed to capture the characteristics that differentiate various targets and activities by extracting relevant features from the time-domain signals. Then, the extracted features were used for classification. We employed the SVM and k-NN algorithms to classify signals based on the identified patterns shown in Figure 1. Through this approach, we could distinguish accurately among different types of targets and their activities, ultimately enhancing the reliability and accuracy of detection systems based on seismic sensors.

3.1 Description of study areas

We collected data from diverse geographical areas. Each area was strategically selected to capture various geological and environmental conditions. The study areas included rural, urban, and natural environments, as shown in Figure 2. These areas were chosen based on the specific objectives of the data collection project, with the objective of the data collection project to obtain a comprehensive understanding of the phenomena being investigated.

Each geophone sensor was integrated into a node unit, which served as a data collection point. The nodes had data storage systems, communication interfaces, and power sources. Thes nodes played a pivotal role in real-time data transmission and storage. Meticulous planning and sensor deployment were crucial during data collection to ensure the accuracy and reliability of the collected information.

We strategically positioned two geophone sensor nodes (Nodes 1 and 2) in each chosen area, creating a well-structured network of data collection points. The sensors (S1, S2, S3, S4, S5, S6, S7 and S8) were carefully installed, with an interval of 2.5 m from one another, to ensure optimal area coverage. We also maintained a consistent 2.5 m gap between two parallel lines of geophone sensors to enhance our ability to detect and analyze events that may cross from one side of an area to another. Such configuration effectively divided the monitored region into segments, allowing us to capture comprehensive ground vibrations and movement data. The data collection area covered a distance of 17.5 m, as shown in Figure 3.



(a) Grass (b) Muddy

(c) Asphalt (d) Soil

Figure 2. Environment of the study areas

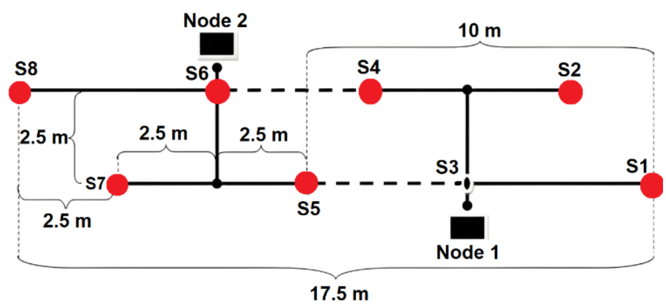
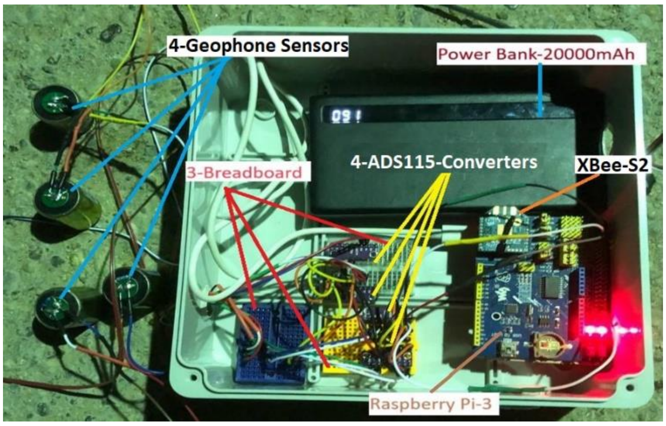


Figure 3. Data collection area

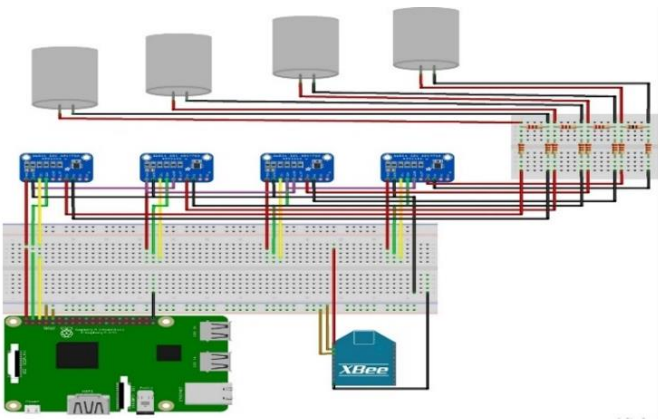
We chose a variety of targets, including humans, animals, motorbikes, and cars. Each target was engaged in multiple activities to ensure a robust dataset. We continuously collected data over a month, enabling us to account for temporal variations and environmental changes. This approach allowed us to comprehensively understand how the aforementioned factors affect seismic signals.

3.2 Nodes for data collection

The data collection nodes served as the backbone of the information-gathering system. They seamlessly bridged the physical aspect of geophone sensors with the digital aspect of data analysis. Each node was meticulously designed. It comprised several essential components, shown in Figure 4(a), to ensure robust data acquisition, storage, and transmission. The core of the data collection node is the Raspberry Pi 3 Model B. It is a versatile and powerful single-board computer that serves as a central processing unit. Given its compact size and energy efficiency, the Raspberry Pi 3 is ideal for field deployments, facilitating data acquisition, storage, and transmission. It works in tandem with the other node components. We integrated four ADS115 ADCs into each node to handle the analog signals from the geophone sensors.



(a) Nodes for data collection



(b) Structure of a node

Figure 4. Design of nodes

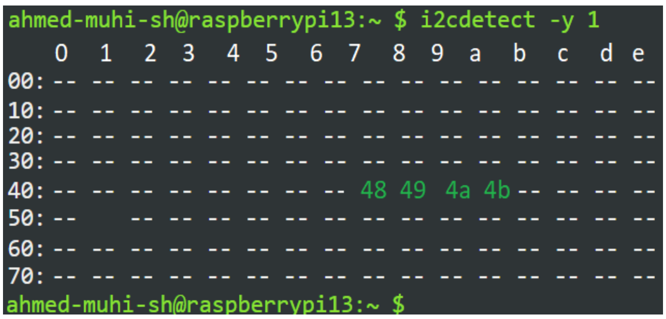
These high-resolution ADCs convert the analog output of the geophone sensors into digital data, which can be processed and analyzed efficiently. Through this setup, vibrations and ground movements detected by the sensors are accurately captured and digitized for further analysis. Each node has an Xbee module for wireless communication and data transfer. This module provides robust and reliable connectivity; thus, it is crucial for transmitting data from remote field locations to a central processing unit. The Xbee module is kept safely inside a protective shell to ensure durability and weather resistance. These characteristics are essential for outdoor installations. A carefully constructed wiring configuration establishes the connection between the Raspberry Pi, Xbee module, and geophone sensors. This wiring configuration enables faultless data exchange between the geophones and the Raspberry Pi, ensuring that every vibration or ground movement is captured accurately. Each node also includes resistors to protect the geophone sensors from potential damage due to electrical surges or other issues, as shown in Figure 4(b).

3.3 Multi-node geophone signal acquisition system

The data acquisition unit consists of three main components: the sensor module, the AD acquisition module, and the computer. The sensor module comprises two nodes equipped with four SM-24 geophone vibration sensors. These geophones have a natural frequency of 10±2.5% Hz, a bandwidth of 10 Hz to 240 Hz, and a sensitivity of 28.8 V/m/s. The sensor module connects to the AD acquisition module via wires.

The AD acquisition module includes three breadboards that house four ADS1115 converters, which are connected to a Raspberry Pi 3 Model B. Data is transmitted to the computer through two XBee-S2 modules: one attached to the Raspberry Pi (sender) and the other to the laptop (receiver). A laptop with a Core i7 processor running Windows 11 is used to configure the Raspberry Pi using the Imager program and the XBee-S2 modules via XCTU software.

Each node is powered by a 20,000 mAh power bank, which provides the required electrical current. Signals from the sensors are collected and synchronized by assigning unique channel addresses (48, 49, 4A, 4B) to each sensor within the node, as depicted in Figure 5. The received analog signals are converted to digital using a 16-bit ADC with a voltage range of ±0.256 V, processed with a gain of 16, and sampled at a rate of 128 samples per second. The digitized signals are then transmitted to the computer via the XBee-S2 modules, with the Raspberry Pi 3 serving as an intermediary.



```
ahmed-muhi-sh@raspberrypi13:~ $ i2cdetect -y 1
     0  1  2  3  4  5  6  7  8  9  a  b  c  d  e
00: -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- --
10: -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- --
20: -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- --
30: -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- --
40: -- -- -- -- -- -- -- -- 48 49 4a 4b -- -- -- --
50: --    -- -- -- -- -- -- -- -- -- -- -- -- -- --
60: -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- --
70: -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- --
ahmed-muhi-sh@raspberrypi13:~ $
```

Figure 5. Addresses for channels

Data were collected over one month at different times across various environments, including mud, asphalt, grass, and soil, at a distance of 17.5 meters, as shown in Figure 3. Eight sensors were deployed, with four sensors assigned to each node, spaced 2.5 meters apart, and each node collected signals simultaneously. Data collection occurred over 10 seconds each time, starting when a target entered the experimental area and continuing until it exited. Each target's activities were recorded 15 times in each environment, resulting in 960 signals per target. The experiment included four targets, each performing different activities across the four environments.

Table 2. Activities of the targets

Object	Activity	Speed	Time
Human	Run, walk	----------	10 s
Car	----------	20 km/h, 10 km/h	
Animal	Run, walk	----------	
Motorbike	----------	10 km/h, 5 km/h	

Data collection was conducted weekly to account for environmental variations, such as changes in mud consistency, soil moisture, asphalt temperature, and water content in grass. In the first week, a person performed two activities—walking and running—while traversing different paths in the experimental area to evaluate detection variability. Signals were recorded as the person moved from the first to the eighth sensor in all four environments. During the second week, signal samples were collected from a car traveling at two speeds, 10 km/h and 20 km/h, in the four environments. In the third week, data were recorded from a motorcycle moving at two speeds, 5 km/h and 10 km/h, in the same environments. In the final week, signals were collected from an animal performing two activities—walking and running—across all environments. In total, 3840 signals were recorded, encompassing all targets, activities, and environments within the one-month experimental period shown in Table 2.

3.4 Signal processing and algorithm

By effectively distinguishing the desired signals from the surrounding noise, signal processing plays a crucial role in enhancing the accuracy of seismic sensor readings. This process involves three key steps: the removal of the direct current component, noise reduction, and normalization [11]. These steps are selected depending on the specific requirements or environmental factors that affect the sensor-generated signals. For example, normalization standardizes measurements and eliminates direct current (DC) components; hence, the accuracy of signal interpretation is improved [24]. Meanwhile, the DC component removal process addresses the inherent baseline bias in signal acquisition instruments to ensure cleaner data. In scenarios where noise originates from the target and the surrounding environment [8], such as mechanical sounds and ambient disturbances, a band-pass filter is used to mitigate these interferences effectively. To further refine signals for analysis, samples from each observation window undergo [23] column-wise normalization using an ADC, producing row vectors with a mean of zero. With this comprehensive approach to signal processing, the reliability and precision of seismic data analysis are optimized.

Our signal processing methodology, implemented in MATLAB, adapts to the varying noise characteristics of the four different environments (asphalt, mud, soil, and grass), as shown in Figure 6, which was used in the experiment.

The key focus was adjusting the amplitude threshold for noise reduction based on the specific environment, while the passband frequency of the high-pass Butterworth filter remained constant across all environments.

The high-pass Butterworth filter was designed with a fixed passband frequency of 10 Hz and a sampling frequency of 30 Hz. The normalized cutoff frequency was calculated as $f_c = F_{pass}/(\frac{F_s}{2})$, where $F_s = 30\,Hz$. Filtering was performed in MATLAB using the filtfilt function to avoid phase distortion, ensuring the temporal integrity of the signals. The amplitude thresholds for detecting the start and end of the signals were set according to the characteristics of each environment. For example, environments with higher noise levels (such as grass and mud) required higher amplitude thresholds to ensure that only meaningful signal data was included in the analysis. These thresholds were defined as T_{start} and T_{end}, and the start and end indices of the detected signal were determined as $i_{start} = \min\{i||x[i]| > T_{start}\}$ and $i_{end} = max\{i||x[i]| > T_{end}\}$.

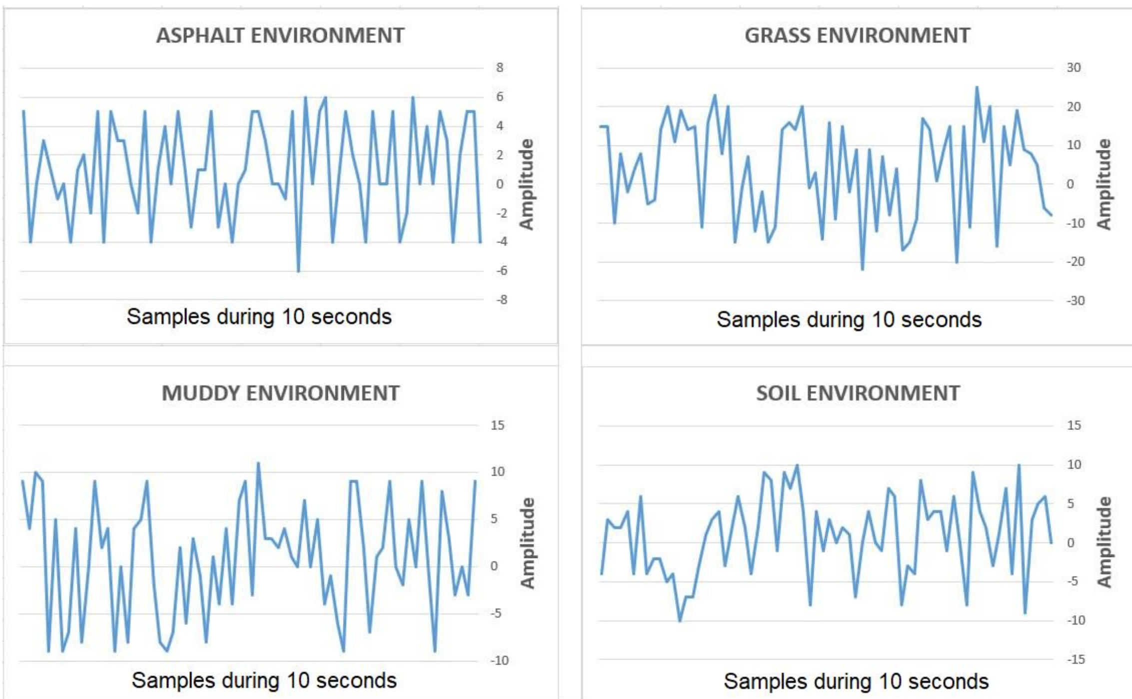


Figure 6. Noise environment without targets

A binary mask $m[i]$ was then created to distinguish the signal of interest from the surrounding noise. This mask was applied to the signal, and the noise estimate was calculated by applying the high-pass filter to the masked signal, expressed as $n[i] = H_{(s)}.(x[i].m[i])$, where $H_{(s)}$ represents the high-pass filter response. Finally, the cleaned signal was derived by subtracting the noise estimate from the original signal: $m[i] = x[i] - n[i]$.

Adjusting the amplitude threshold according to the environmental conditions while maintaining a constant passband frequency effectively mitigates noise without altering the detected signals within the detection range. The processed signals were then saved for further analysis.

We chose time-domain features because they directly capture the essential characteristics of the geophone signals, reflecting both amplitude and statistical properties without the complexity of transformations. This approach is ideal for distinguishing different activities and environments. The seven features—mean, standard deviation, minimum, maximum, median, skewness, and kurtosis—were selected to describe the signal comprehensively. The mean and standard deviation capture the average and variability of the signal, while the minimum and maximum values highlight extreme points. The median provides a robust central measure, and skewness and kurtosis describe the shape of the signal's distribution, revealing asymmetry and the presence of outliers, as shown in Eq. (1).

Normalization was applied using Standard Scaler to ensure all features were on the same scale, preventing larger values from dominating the analysis. This step improves the performance of machine learning models by making all features comparable and ensuring balanced contributions from each feature.

$$\boldsymbol{X} = \begin{bmatrix} \boldsymbol{mean_1} & \boldsymbol{std_1} & \boldsymbol{min_1} & \boldsymbol{max_1} & \boldsymbol{median_1} & \boldsymbol{skew_1} & \boldsymbol{kurtosis_1} & \dots & \boldsymbol{env1_1} & \boldsymbol{env2_1} & \dots & \boldsymbol{act1_1} & \boldsymbol{act2_1} \\ \boldsymbol{mean_2} & \boldsymbol{std_2} & \boldsymbol{min_2} & \boldsymbol{max_2} & \boldsymbol{median_2} & \boldsymbol{skew_2} & \boldsymbol{kurtosis_2} & \dots & \boldsymbol{env1_2} & \boldsymbol{env2_2} & \dots & \boldsymbol{act1_2} & \boldsymbol{act2_2} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots \\ \boldsymbol{mean_n} & \boldsymbol{std_n} & \boldsymbol{min_n} & \boldsymbol{max_n} & \boldsymbol{median_n} & \boldsymbol{skew_n} & \boldsymbol{kurtosis_n} & \vdots & \boldsymbol{env1_n} & \boldsymbol{env2_n} & \vdots & \boldsymbol{act1_n} & \boldsymbol{act2_n} \end{bmatrix} \quad (1)$$

One-hot encoding was applied to the categorical variables 'environment' and 'activity', which were normalized, resulting in $\boldsymbol{X_{norm}}$. Then, the dataset was divided into training and testing sets, with 80% of the data used to train the models and 20% used to test them. The SVM model was also trained and evaluated, and its mean accuracy was computed as Eq. (2):

$$Accuracy_{svc} = \frac{1}{|X_{test}|} \sum_{i=1}^{|X_{test}|} 1\left\{\hat{y}_{svc,i} = y_{test,i}\right\} \quad (2)$$

where, $|\boldsymbol{X_{test}}|$ is the number of test samples, $\boldsymbol{\hat{y}_{svc,i}}$ is the predicted labels and $\boldsymbol{y_{test,i}}$ is the actual labels. Similarly, the k-NN model was trained and evaluated, and its mean accuracy was presented by Eq. (3):

$$Accuracy_{knn} = \frac{1}{|X_{test}|} \sum_{i=1}^{|X_{test}|} 1\left\{\hat{y}_{knn,i} = y_{test,i}\right\} \quad (3)$$

Which measures how well the class labels of the test data are correctly predicted by the model. This variable is calculated by comparing the predicted labels with the actual labels. Finally, model performance is assessed across different data divisions by applying k-fold cross-validation. The mean accuracy for k-NN over k folds is calculated using the following equation: $\text{Average Test Accuracy}_{knn,svm} = \frac{1}{k}\sum_{j}^{k} 1\,\text{Accuracy}_{knn,svm}^{j}$. Accordingly, the reliability and generalization of the models are guaranteed.

4. RESULTS

This section presents the results regarding the effects of different environments on the signals generated by geophone sensors and the effect of various activities of each target across all the environments. In addition, the analysis includes signal detection for each target at each point under different activities and environments based on the data rate of 128 used in the experiment. Moreover, the signal displays the signal processing outcomes with the model evaluation results.

As shown in Figure 7, grass environments tend to exhibit high signal amplitudes because of their flexible surface. Meanwhile, soil and muddy areas present moderate values. By contrast, asphalt surfaces typically yield low signal amplitudes for the same reason. Such differences show how surface characteristics play a crucial role in shaping signal propagation and detection outcomes.

Table 3 provides the activity-specific results for each target in an environment for the maximum signal amplitude. The aforementioned values show that the amplitude of the waves generated by an animal is higher during running than during walking. This result is consistent in nearly all environments. The amplitude of the waves generated by humans is also similar to that of animals in nearly all environments. For the car, the results of the experiments indicate that the lower the car speed, the higher the wave amplitude and this finding is observed at a speed of 10 km/h compared with a speed of 20 km/h in nearly all the environments. For the motorbike, a lower speed results in greater wave amplitude. Abnormal ratios are found in the motorbike (±76.96%, ±61.20%) and animal (±96.20%, ±96.68%) in the grassy environment, and the human (±23.90%, ±24.21%) and car (±22.34%, ±19.16%) in the muddy environment. These apparent differences are attributed to only two environments: clay and grass. This finding can be attributed to variations in water content caused by the different time periods during which the data were collected. Data were collected within a month and under different conditions. This change in water percentage might have affected wave amplitude.

In the experiments conducted in various environments and with distinct objectives, each target performed activities that corresponded to a specific endeavor. The running activity, which showcased an individual aged 35 years and weighing 74 kg, served as the focal point. Data collection was performed across four diverse environments, namely, grass, mud, asphalt and sand, with a consistent frequency of 10 Hz and a data rate of 128 samples per second. Notably, the running activity yielded significantly greater distances compared with the walking activity. The configuration of detection points is shown in Figure 8. The vibration sensor signal is detected at two nearby locations, indicating the running stance of the human target.

Table 3. Amplitude for each target's activity

Environment	Targets							
	Animal		Human		Car		Motorbike	
	Run	Walk	Run	Walk	Speed 20 km/h	Speed 10 km/h	Speed 10 km/h	Speed 5 km/h
Grass	±96.20 %	±96.68%	±81.28%	±74.61%	±81.37%	±82.48%	±76.96%	±61.20%
Muddy	±28.37%	±22.96%	±23.90%	±24.21%	±22.34%	±19.16%	±17.69%	±20.55%
Soil	±16.47%	±14.88%	±14.87%	±14.56%	±15.35%	±15.63%	±13.16%	±14.73%
Asphalt	±14.40%	±10.28%	±12.66%	±11.04%	±8.21%	±9.56%	±6.05%	±7.53%

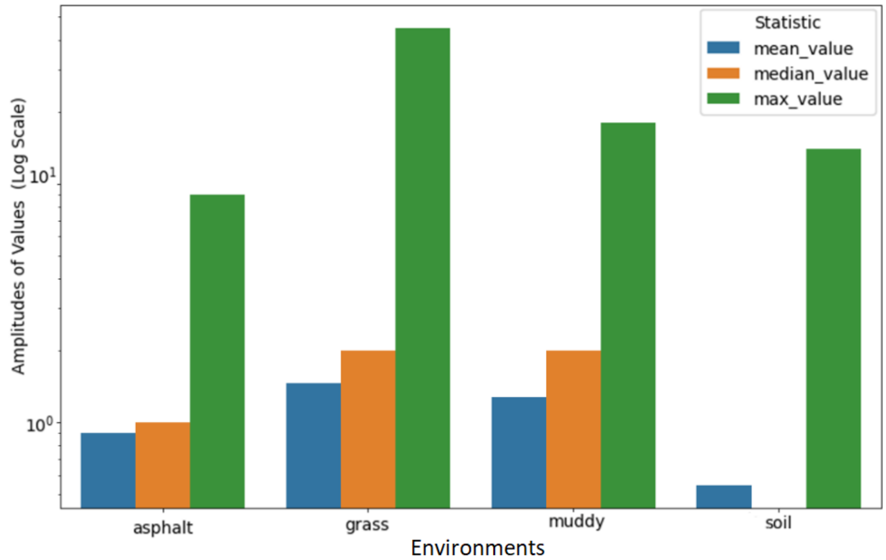


Figure 7. Amplitude for each environment

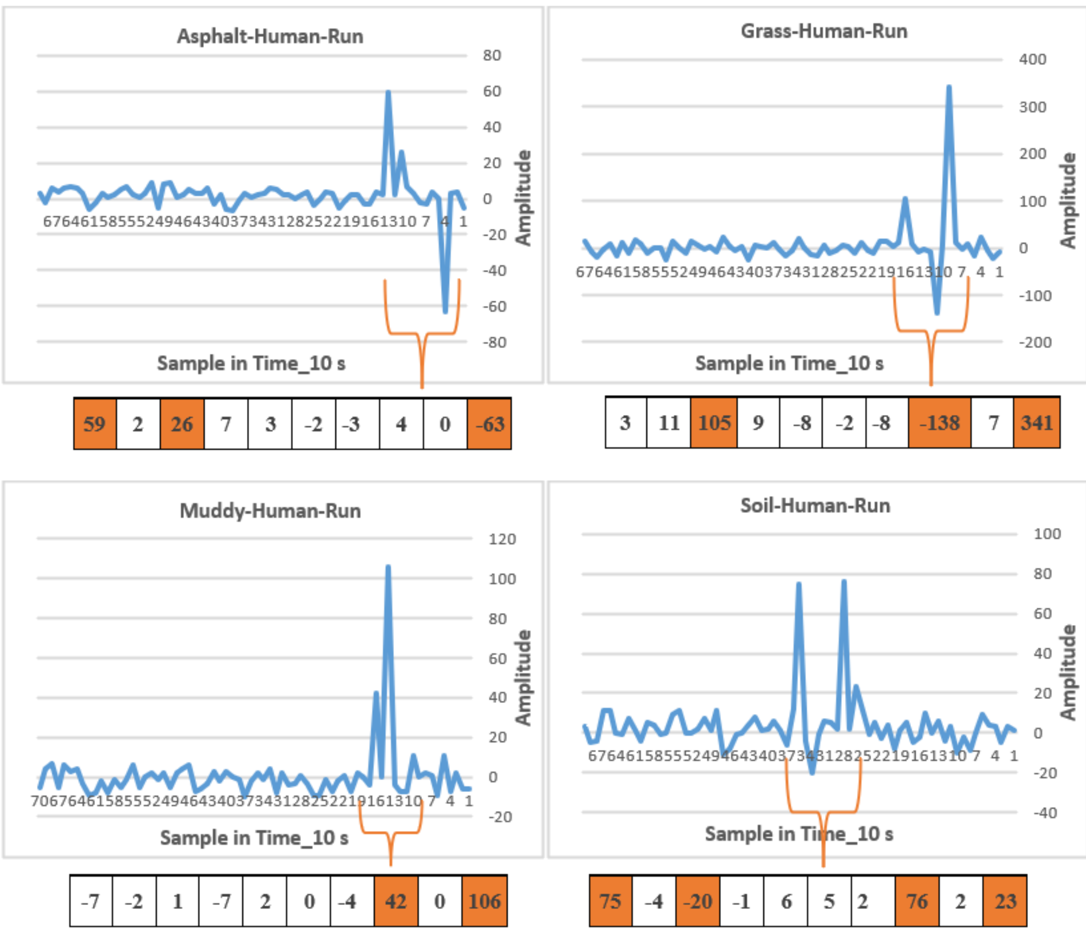
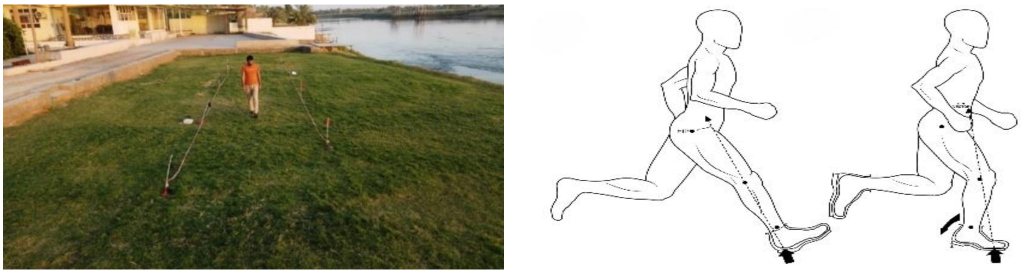


Figure 8. Detection of running human

The ground contact pattern begins predominantly at the posterior part of the foot, indicating initial heel contact, which is typical during dynamic movements. This is followed by a distinct void in the signal, representing the plantar fascial area where the foot arch momentarily reduces direct contact with the ground. The contact then progresses towards the anterior part of the foot, suggesting toe engagement as the movement transitions. The prolonged duration of the signal indicates a shift in activity, where the individual transitions from running to jumping. This extended contact phase highlights the biomechanical adjustments made during this motion, as illustrated in Figure 9. These observations reveal dynamic pressure distribution and foot-ground interaction timing.

Notably, assessing the same individual in walking disparate areas exhibits closer proximities than those observed during running, as illustrated in Figure 10.



(a) Real person (b) Human model

Figure 9. Real person and the human movement model in our explement

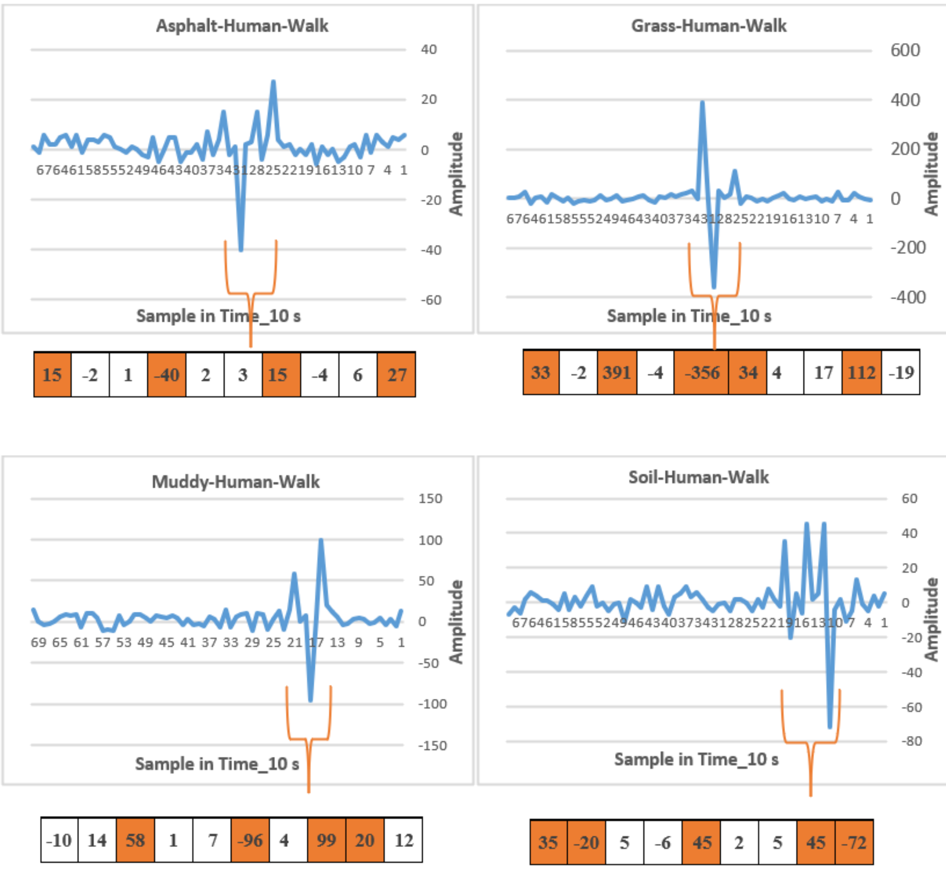
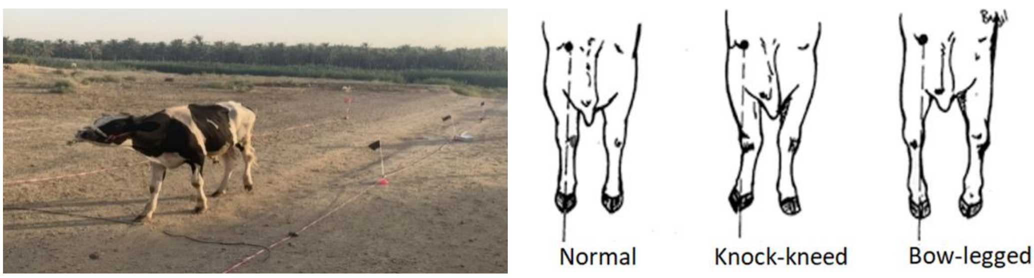


Figure 10. Detection of walking human



(a) Real cow (b) Animal model

Figure 11. Real cow and model that represents animal movement in our experiment

The following experiment involved a cow that weighed around 140 kg. It was chosen to represent various environments (grass, asphalt, mud, and soil). Data were collected using a geophone S-24 sensor, with recordings at a frequency of 10 Hz for two activities: walking and running.

As shown in Figures 11(a) and 11(b), animals have more legs in contact with the ground, and their hooves produce distinct signals compared with human feet, offering unique insights into ground pressure distribution and vibration patterns.

The nature of walking is similar between humans and animals, although differences exist due to the structure of the limbs and the number of legs. Based on experience, stride is shorter in animals when running because the distance between their legs is shorter, as shown in Figure 12.

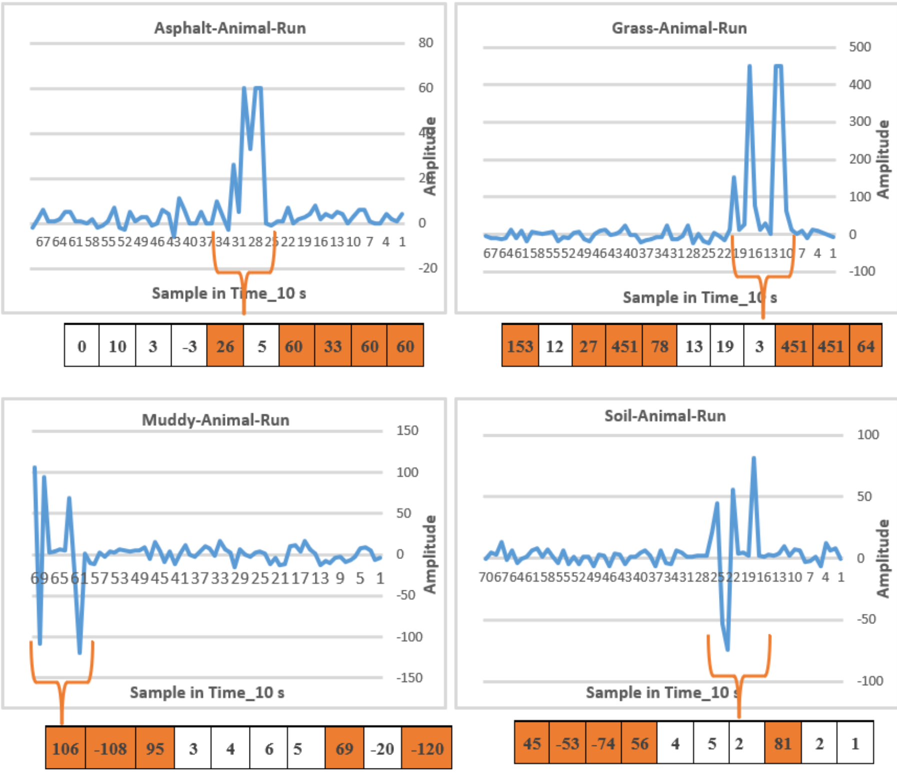


Figure 12. Detection of running animal

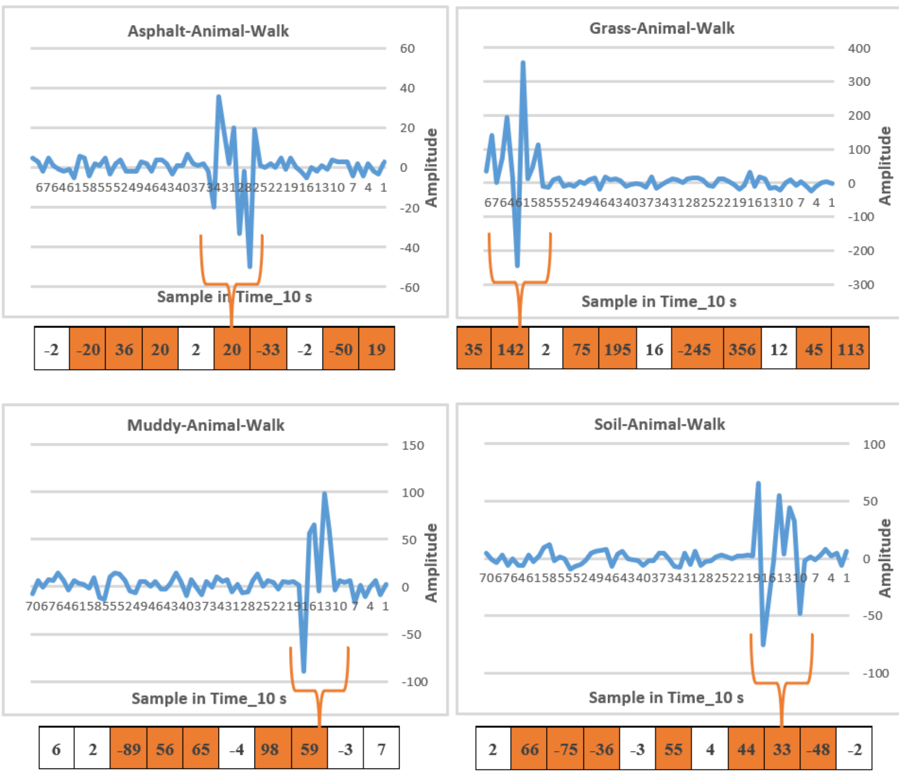
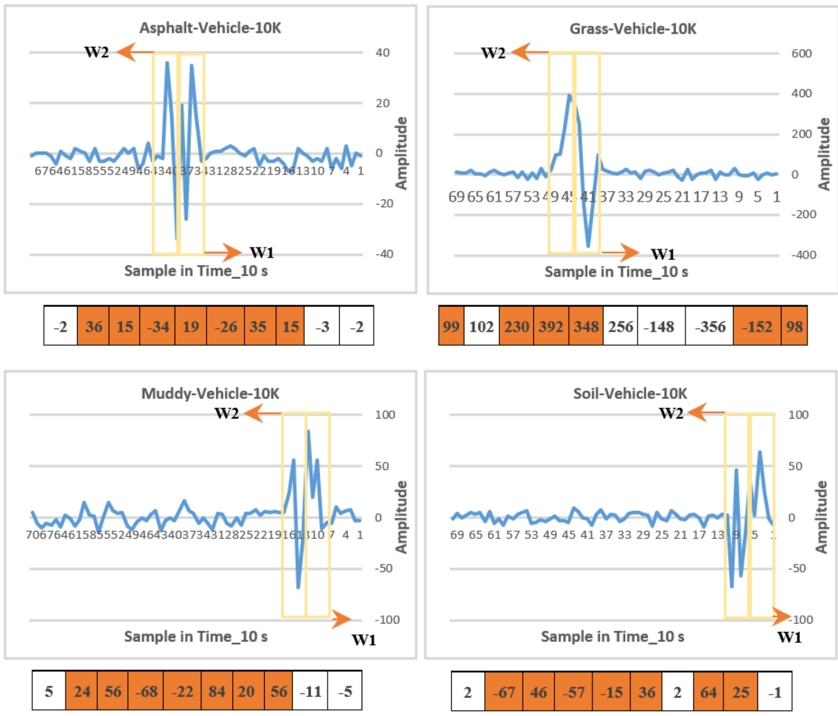


Figure 13. Detection of walking animal

(a) Real car (b) Car model

Figure 14. Real car and car model in our experiment



(a) 10 km/h

(b) 20 km/h

Figure 15. Detection of target car at 10 km/h and 20 km/h

By contrast, animals' legs touch the ground more frequently than humans when walking because animals have more legs, as shown in Figure 13. Furthermore, we consistently observed that the signal generated by an animal while running surpassed that while walking in all the conducted tests, as previously stated.

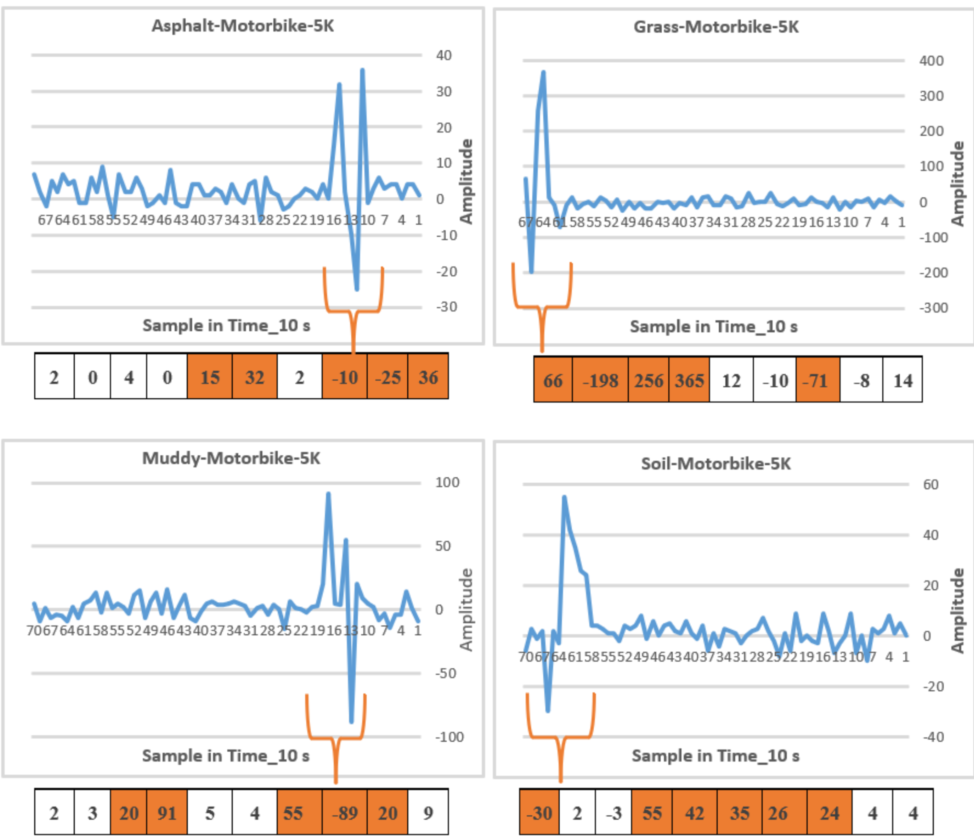
Meanwhile, the car also underwent testing in various environments, including asphalt, mud, sand and grass, at two speeds: 10 km/h and 20 km/h. Data were collected using eight sensors (SM-24 geophone sensor), which were installed along the proposed route at a frequency of 10 Hz. As shown in Figures 14(a) and 14(b), the test period took 10 s for each speed.

In the experiment, interruptions during the detection period were generally minimal, ensuring a high level of signal clarity for analysis, as illustrated in Figure 15. The sensors, designated as W1 for the front wheels and W2 for the rear wheels, successfully detected signals that directly corresponded to the pressure exerted by the wheels under varying conditions and speeds. These signals provided clear insights into the force dynamics between the wheels and the surface. A consistent pattern was observed across all environments: the wave amplitude was significantly higher when the vehicle was moving at a speed of 10 km/h. This suggests that lower speeds allow for more pronounced pressure impact detection by the sensors, likely due to longer contact durations and less dynamic load distribution. Conversely, at a speed of 20 km/h, the wave amplitude was consistently lower, reflecting reduced detection sensitivity at higher speeds due to shorter contact times and potentially more diffused pressure distribution. This trend is clearly depicted in Figures 15(a) and 15(b).

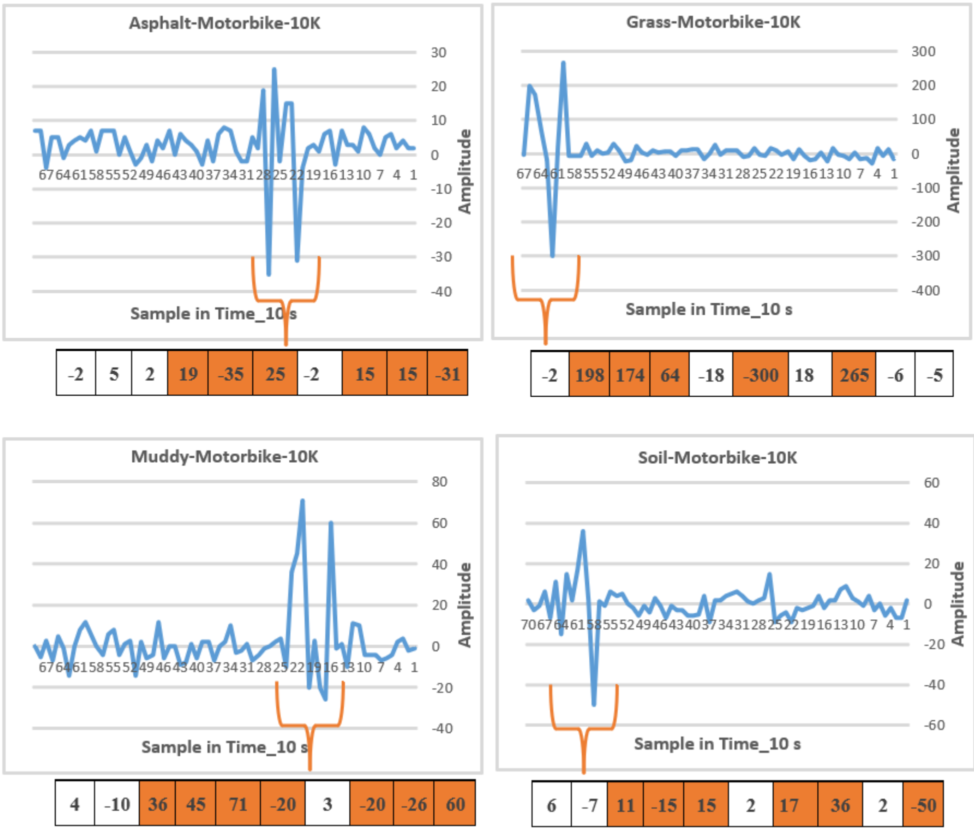
During the data collection experiment, data from the seismic sensors were received for 10 s in four environments: muddy, asphalt, sand and grass. The experiment was conducted on a motorbike at 5 km/h and 10 km/h, covering the specified areas, as shown in Figure 16. The spacing between detection points, influenced by the data rate of 128 samples per second, was varied in this work. In addition, a significant observation was made regarding signal amplitude; that is, signal amplitude was higher at a speed of 5 km/h in nearly all the environments compared to 10 km/h, as depicted in Figures 17(a) and 17(b).

Processing was conducted only in areas outside the detection range. We aimed to utilize the resultant detection signal without any modifications. Figure 18 displays three distinct signals. The first signal represents the original output of the seismic sensor (i.e., the original signal). The second signal denotes the noise percentage detected in the data (i.e., estimated noise). The third signal indicates the outcome after processing (i.e., signal after noise reduction). The y-axis represents signal amplitude, while the x-axis represents the number of signals received within a 10-second interval.

Figure 16. Actual motorbike in our experiment



(a) 5 km/h



(b) 10 km/h

Figure 17. Detection of target car at 5 km/h and 10 km/h

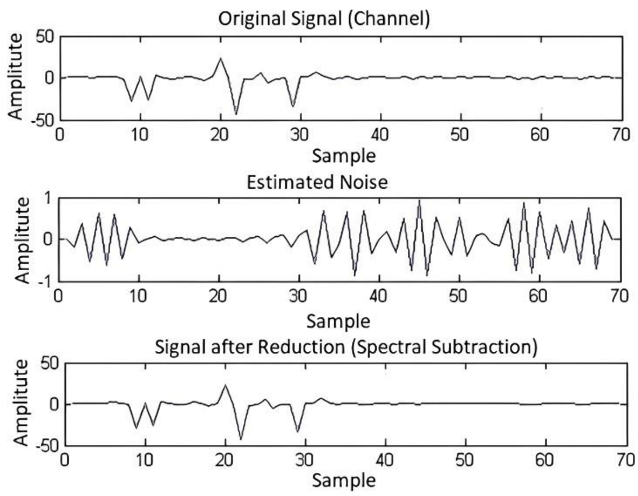
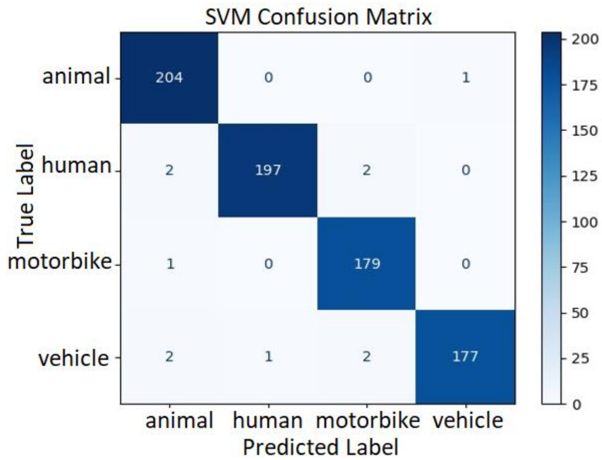


Figure 18. Signal processing for detection regain

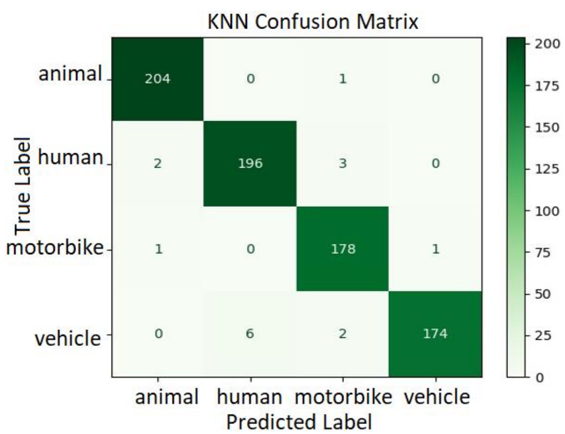
The SVM model demonstrated strong stability, achieving an average cross-validation score of 98.36% and an accuracy of 98.57%. As shown in Table 4, it excelled in precision (0.97 to 1.00) and achieved a maximum F1 Score of 0.98. The 'Animal' class had the highest recall (0.99), particularly valuable in applications requiring minimal false negatives, such as wildlife monitoring or medical diagnostics.

Table 4. Class evaluation

Class	Precision	Recall	F1-Score
Animal	0.97	0.99	0.98
Human	0.95	0.97	0.96
Motorbike	0.96	0.96	0.96
Vehicle	1.00	0.95	0.97



(a) SVM



(b) k-NN

Figure 19. Confusion matrices for SVM and k-NN

The k-NN model also showed solid performance, with a cross-validation score of 96.80% and training/testing accuracies of 98.76% and 96.88%. Its precision, recall, and F1 Score metrics were consistently high, making it a reliable model. However, the 'Human' class displayed slightly lower precision (0.95) than SVM, leaving room for refinement. Future studies could use confusion matrices to understand better misclassification patterns, particularly in overlapping categories like 'Motorbike' and 'Vehicle.' This insight further enhances the model's ability to differentiate between similar classes, as shown in Table 4.

The confusion matrices highlight the performance of SVM and k-NN across four classes: Animal, Human, Motorbike, and Vehicle, as shown in Figures 19(a) and 19(b). SVM demonstrated superior accuracy, with minimal misclassifications. For example, the Animal class achieved 204 correct predictions with only one misclassification, while the Human class showed excellent precision and recall (0.99) with just two errors. Similarly, the Motorbike and Vehicle classes had high accuracy, with only minor misclassifications. k-NN performed well but had slightly higher error rates. While the Animal class matched SVM's performance, the Human class saw more misclassifications, reflecting challenges with overlapping features. Motorbike and Vehicle classes also showed increased confusion compared to SVM.

Overall, SVM outperformed k-NN, but k-NN's simplicity and solid accuracy make it viable for specific tasks. Future work could refine k-NN's handling of overlapping classes and explore ensemble methods to improve both classifiers' robustness.

5. DISCUSSION

Generally, researchers need to provide more detailed explanations of signals produced by seismic sensors for detecting targets. This hesitancy arises from the inherent variability in signals produced by targets during data collection. This variability can be significantly influenced by environmental factors or noise originating from the environment or the target, such as sounds or movements. Seismic sensors are susceptible to sudden events and other occurrences. This condition may considerably affect the generated signals because of their ability to detect any movements within their sensitivity range in a given environment. The residential or rural setting and the surface from which the signal is collected are crucial factors in determining signal characteristics. After acknowledging these challenges, we chose to undertake a comprehensive approach to signal collection and analysis. This approach involved collecting data from various environments, using different entities as targets, and engaging in diverse activities to fully capture the details of the signals as they are encountered. This approach aimed to provide a deep understanding of the capabilities and limitations of the sensors. Although the signals were visually similar, a meticulous analysis revealed precise detection of impact points within the required exploration time frame. The variations in signal amplitudes across different environments and detection categories could be ascribed to the flexible nature of surface materials.

In the study by Khaleghian and Taheri [14], a robot was observed across surfaces, including grass, concrete, soil, and asphalt, revealing varying radial acceleration signals, particularly below 20 Hz. The initial slip ratios also differed, with higher friction surfaces exhibiting lower ratios at equivalent speeds. Grass achieved the highest slip amplitude, followed by concrete, soil, and asphalt. In the study by DuPont et al. [13], the laser line striper, developed at Carnegie Mellon University, presented varying spatial frequency responses across surfaces mounted on a robot; grass obtained the highest magnitude, followed by sand, gravel, and asphalt. Dupont et al. [25] utilized robot vibrations to collect magnitude frequency responses by using proprioceptive sensors. Four simplifying assumptions were made: the robot's center of gravity, body mass, motion limited to small angles, and tires that maintain ground contact. The results showed higher responses on asphalt, followed by dirt, mud, and grass.

During our experiment on human activities, running exhibited a higher signal amplitude than walking. In the study by Ghosh et al. [8], the seismic sensor detected a peak voltage of nearly two mV in human running, a significant increase compared with human walking, which was less than 5e-4 V. This finding indicated a fourfold increase in peak ground velocity during running. Furthermore, in some studies [26, 27], several gait parameters exhibited monotonic changes with escalating speed during walking and running. Such alterations included heightened step length, cycle duration, and reduced stance duration [28, 29]. This transition was marked by a sudden reduction of 35% in ground contact time and a surge of 50% in peak ground reaction force. Such abrupt changes highlighted the amplification of signals during running, as hypothesized previously.

Moreover, the difference in amplitude occurred at various car speeds. In previous research [30], realistic displacement amplitudes were obtained after applying an improved processing procedure to the processed pulse signal corresponding to a single axle load at speeds of 35 km/h and 70 km/h and vertical displacement amplitudes of 0.1, 0.3, and 1 mm. Notably, the signal amplitude at 35 km/h was higher than that at 70 km/h.

Analysis revealed some similarities between the signal patterns generated by animal and human targets, corroborating previous comparative studies [31, 32]. However, significant differences are also evident, particularly in the number of legs and the structure of feet. Animals have more feet in contact with the ground, and their hooves generate signals that differ from those produced by human feet. Although similarities exist, notable variations occur in the distances between successive detection during running, which are shorter in animals than in humans. In addition, the space between the legs is less, similar to that in walking dogs [33], although some differences occur due to the unique nature of animal hooves. This characteristic also affects the walking pattern of animals, where all four legs come in contact with the ground nearly simultaneously, with overlapping distances [34].

At a speed of 10 km/h, the wave amplitude of the car was consistently higher across all environments but was lower at approximately 20 km/h [10]. This phenomenon can potentially be explained by considering the vector amplitude of the car's speed. Our experiments verified that vector amplitude was smaller at higher speeds. This finding is aligned with our observations across various environments [30]. In some instances [35], however, the wave amplitude at the car's speed was greater than at a slower speed, contrasting with the general trend. Such inconsistency can be attributed to several factors, including the friction between the car's tires and the ground, the car's load during the experiment, and the nature of the ground. For example, the car may produce signals that differ from the expected norms when heavily loaded [14, 25]. In addition, the roughness of the tires and the speed at which the signal reflects off the ground are crucial for determining the observed wave amplitudes. Accordingly, this issue remains a subject of ongoing research. To increase the understanding of these complexities, researchers may conduct experiments under various environmental conditions using different types of tires with varying roughness levels and vehicle loads. This comprehensive approach will help clarify the interplay of factors that affect wave amplitudes in vehicle detection systems.

Moreover, such differences can be attributed to the weight disparity between cars and the size of their wheels compared with those of a motorbike. The car's larger wheels [36] resulted in more detection points, as reported by Ashhad et al. [37]. The discrepancy in detection signals between the car and the motorbike remained evident even though audio signals were employed to detect targets.

The findings presented in this study have significant practical implications for improving seismic sensor-based security systems. By capturing the variability of signals across different environments and target types, this work provides a foundation for enhancing the reliability and robustness of these systems in real-world deployments. For instance, understanding the sensitivity of seismic sensors to varying surface types and movement patterns can inform the design of algorithms that better distinguish between human, animal, and vehicle activities, thereby reducing false alarms in diverse settings. Additionally, the insights into amplitude variations with speed and surface flexibility can guide the development of adaptive thresholding techniques tailored to specific deployment environments. Despite these advancements, the study has limitations, such as the inherent dependency on environmental and surface conditions that may introduce signal noise or distortions. Future research could mitigate these challenges by employing advanced signal processing techniques and machine learning models to enhance feature extraction and classification accuracy. Moreover, conducting experiments under controlled conditions with a broader range of target types, surface materials, and environmental scenarios could provide a deeper understanding of sensor performance. This approach not only enables the development of standardized protocols for deploying seismic sensors in security applications but also ensures consistent performance across various scenarios. By establishing clear guidelines for sensor placement, signal processing, and interpretation, it enhances the scalability of these systems to cover larger areas or diverse environments effectively.

6. CONCLUSION

This research presents a different direction in understanding the variation of signals generated by seismic sensors in terms of different environments (asphalt, soil, grass, and mud) and targets (human, animal, motorbike, and car), along with the activities that distinguish each target, to provide a clear visualization of the signals generated by sensors.

Researchers often avoid providing detailed explanations of seismic sensor signals for target detection due to signal variability resulting from environmental factors or noise, including sounds or movements. Seismic sensors are susceptible to sudden events. They detect movements within their range and are influenced by setting and surface-type factors. To address these issues, we collected diverse data to improve the understanding of sensor capabilities. Despite the similarity among the initial signals, a detailed analysis revealed precise detection of impact points within the exploration time frame.

In summary, the k-NN and SVM models yielded robust classification results. SVM achieved an accuracy of 98.57%, exhibiting its superior performance in binary classification. Meanwhile, k-NN achieved an accuracy of 96.88%, demonstrating its versatility in multi-class scenarios. Future optimization efforts can focus on leveraging ensemble methods and hyperparameter fine-tuning to enhance classification accuracy further.

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