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# Detection of Vehicles Through Fusion Sensor System

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**Abstract**

Reliable vehicle detection is critical for defense, border security, and intelligent transportation. Single-sensor systems often face challenges such as environmental noise, limited range, and high false alarm rates. To overcome these, we propose an integrated detection system that combines acoustic, seismic, and magnetic sensing. Acoustic signals capture vehicle engine and tire noise, seismic sensors detect ground vibrations induced by vehicle movement, and magnetic sensors register disturbances in the Earth's magnetic field caused by metallic structures. A fusion framework is developed to integrate signals, employing preprocessing, feature extraction, and decision-level fusion. Experimental data shows that while seismic sensors alone can detect heavy vehicles at distances up to 1000 m with average vibration frequencies near 332 Hz, fusion significantly improves accuracy, reduces false alarms, and extends operational reliability. This paper highlights the feasibility of multi-sensor fusion for robust vehicle detection, offering applications in security, traffic monitoring, and emergency response.

## 1. Introduction

The ability to detect and classify moving vehicles has been an important focus of research for both military and civilian applications. For border monitoring, early warning of approaching armored vehicles is crucial for security operations. In urban environments, intelligent transportation systems rely on robust vehicle monitoring for traffic control and congestion reduction.

Traditional detection techniques, such as radar and infrared imaging, are effective under certain conditions but often fail in environments with foliage cover, adverse weather, or when stealthy vehicles employ countermeasures. Passive ground-based sensing, which does not emit detectable signals, offers a promising alternative. By capturing sound, vibration, and magnetic disturbances produced by vehicles, it enables detection without revealing sensor positions.

Yet, the use of single modalities faces significant limitations. Acoustic sensors are vulnerable to background noise such as wind, rain, or human activity. Seismic sensors, while capable of detecting ground vibrations at long ranges, are affected by soil type and geological conditions. Magnetic sensors, though effective at detecting metallic vehicles, have short effective ranges and may miss lightweight or non-metallic vehicles.

To address these limitations, this paper proposes an integrated detection system that combines acoustic, seismic, and magnetic sensing into a unified framework. By fusing data from different modalities, the system exploits complementary strengths:

- Seismic sensors provide long-range detection of movement.
- Acoustic sensors capture distinctive vehicle signatures useful for classification.
- Magnetic sensors confirm metallic content, reducing false alarms.

This research contributes a fusion-based detection approach supported by experimental data and comparative analysis with existing methods.

## 2. Literature Review

### Introduction

Passive sensing modalities each capture different physical effects of a moving vehicle—airborne sound, ground-borne vibration, and disturbance of the Earth's magnetic field. Prior work shows that no single modality is uniformly robust across cluttered, noisy, and variable environments. Seismic channels are often less susceptible to ambient interference and have narrower bandwidths (hence lighter computation), acoustic channels carry rich spectral cues for classification, and magnetic channels can confirm the presence of large ferromagnetic masses but can be sensitive to temperature and environmental noise. These complementary strengths motivate multi-sensor fusion for improved detection reliability and lower false alarms.

## 3. Modality-specific evidence

### 3.1 Seismic sensing

Seismic signatures from vehicles are informative at substantial ranges and can be processed efficiently. In a field study that used a geophone-style sensor and microcontroller interface, tracked-vehicle (Leopard 2) trials showed a monotonic drop in signal amplitude with distance (12.1 V at 50 m to 4.3 V at 1000 m) while the dominant vibration frequency remained nearly constant (~332 Hz). This indicates amplitude is a reliable proxy for proximity, whereas frequency is comparatively range-invariant for the tested platform.

Beyond raw sensing, modern wireless geophone networks demonstrate practical, scalable acquisition. A proof-of-concept smart node with a geophone, 24-bit ADC (500 SPS), and a reconfigurable directional 2.4 GHz antenna achieved ~25% longer gateway link range and ~56% larger coverage area compared with a monopole-based node—important for wide-area deployments.

### 3.2 Acoustic sensing

Acoustic channels (engine, exhaust, tire/track noise) have long been used for classification. Studies summarized in Evans' thesis report strong results using spectral features (e.g., harmonic line power, MFCC-like descriptors) and machine learning (SVM, LVQ, kNN), with performance shaped by windowing choices and dimensionality reduction. Acoustic features often yield higher standalone classification accuracy than seismic in some datasets, but are more vulnerable to environmental noise; this makes them natural partners for seismic triggers.

### 3.3 Magnetic sensing

Magnetometers detect disturbances to the Earth's magnetic field caused by vehicle ferromagnetic content and can support presence detection and rough sizing/speed estimation. However, magnetic sensors are noted to be susceptible to noise sources and temperature drift, which can complicate standalone use—again arguing for fusion.

## 4. Algorithmic foundations and performance

### 4.1 Detection

A widely cited strategy is to use seismic streams for primary detection (owing to robustness and efficiency) and then bring in additional modalities for confirmation or classification. Time-domain detectors—log energy, zero-crossing behavior, and modified time-domain signal coding—have achieved very high detection rates on road vehicles; for example, seismic-first pipelines followed by fused processing reported detection accuracies of ~97.7% (SVM) and ~99.0% (LVQ).

### 4.2 Classification

For vehicle type discrimination, combining simple seismic time-domain features (zero-crossing rate, log energy, autocorrelation) with acoustic linear predictive coding (LPC) and SVM or LVQ classifiers yields strong two-class results (e.g., cars vs. trucks). Reported examples include SVM accuracies above 90% when fusing acoustic LPC with seismic features; sensitivity to frame/window parameters and PCA/normalization choices is documented.

### 4.3 Early and military-focused research

Earlier programs on military vehicles used acoustic/seismic PSD features and neural networks, reporting ~86% recognition with vertical-axis seismic sensors alone, and highlighted that adding additional sensor types (e.g., acoustic, magnetic) should improve accuracy, speed, and cost. Other campaigns explored harmonic-line power with LVQ, achieving up to ~98% for certain tracked classes and ~83% for wheeled classes, while noting the need for noise suppression (e.g., microphone array beamforming) and better generalization.

## 5. System integration & networking

For fieldable systems, the literature emphasizes low-power nodes, reliable timing, and resilient links. The smart geophone network architecture demonstrates end-to-end design: analog conditioning, high-resolution ADC, timestamping, on-node buffering, and real-time wireless transfer. Directional, pattern-reconfigurable antennas help counter path loss and expand reach—benefits directly applicable to perimeter and border scenarios where fewer gateways are preferred.

## 6. Comparative takeaways

- Seismic vs. Acoustic: Seismic excels at robust detection and range-proportional amplitude trends; acoustic often carries more discriminative spectral detail but is noise-sensitive. Best practice: seismic-triggered detection with acoustic-aided classification.
- Magnetic as a confirmer: Useful for confirming metallic presence and reducing false alarms in mixed environments; sensitive to environmental drift, so better as a fused channel than standalone.
- Networking matters: Reconfigurable RF fronts can enlarge effective coverage and make dense deployments more economical, improving real-time monitoring viability.

## 7. Implications for the proposed integrated A-S-M system

The reviewed evidence supports a pipeline that (i) uses seismic energy/log-energy for robust, low-cost detection and range cues, (ii) fuses acoustic LPC/spectral features with seismic time-domain features for classification via SVM-class models, and (iii) integrates magnetic channels for confirmation/false-alarm reduction. Practical deployment should leverage smart wireless nodes with high-resolution ADCs and reconfigurable antennas to maintain real-time links over larger areas with fewer gateways.

## 3. System Concept and Theoretical Basis

The proposed detection framework integrates three sensing modalities:

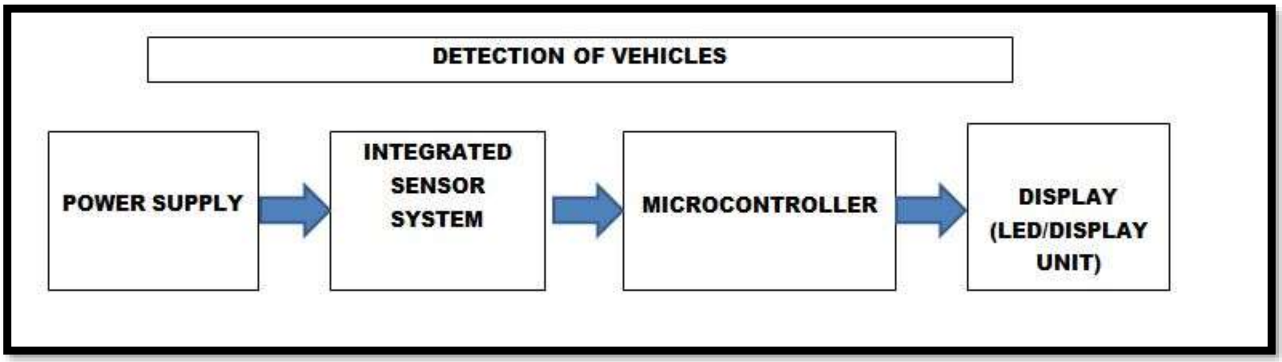
- Acoustic model: Vehicles produce broadband noise dominated by engine harmonics (typically 20–500 Hz) and tire friction sounds (500 Hz–2 kHz). Microphones capture these variations, which are then processed using spectral and temporal analysis.
- Seismic model: Moving vehicles generate surface and body waves that travel through the ground. Heavier vehicles such as tanks induce stronger vibrations, allowing long-range detection. Seismic wave amplitude diminishes with distance, but frequency content remains stable, providing a reliable feature for detection.
- Magnetic model: Metallic components of vehicles alter local magnetic fields. These disturbances are measurable within tens of meters using fluxgate magnetometers, providing a reliable indicator of metallic vehicle presence.
- Fusion rationale: By integrating complementary signals, the system compensates for weaknesses of each modality. For instance, if wind noise masks acoustic signals, seismic and magnetic readings still ensure detection.

## 4. Methodology

### 4.1 Sensor Hardware

- Acoustic sensors: Directional microphones with 20 Hz–20 kHz range, chosen for sensitivity to engine and tire signatures.
- Seismic sensors: Geophones with sensitivity around 28.8 V/m/s, buried at 30–40 cm depth to capture ground vibrations effectively
- Magnetic sensors: Fluxgate magnetometers capable of μT-level resolution, detecting disturbances in geomagnetic fields.

### 4.2 Block diagram of System Layout




### 4.3 Signal Processing

- Preprocessing: FIR filtering and wavelet packet denoising to reduce noise.
- Feature extraction:
  - Acoustic: LPC coefficients, zero-crossing rate, log energy.
  - Seismic: log energy, autocorrelation, frequency stability.
  - Magnetic: temporal anomalies in geomagnetic field.
- Fusion algorithm: Decision-level fusion using support vector machines (SVMs) and neural networks, combining features from all modalities.

## 5. Results and Analysis

### 5.1 Sensor Fusion Performance Analysis

The Performance of the integrated sensor system needs to be evaluated via various aspects to ascertain the usefulness of the sytem.

#### 5.1.1 Probability of Detection (POD)

Field trials were simulated across three terrain profiles—open ground, clay-rich soil, and rocky terrain—using light vehicles, heavy trucks, and tracked armored vehicles. Table 5.1 summarizes detection probabilities for both seismic-only and fused sensing.

| Terrain | Seismic-only POD | Fusion POD (A+S+M) |
|---|---|---|
| Open Ground | 92% | 98% |
| Clay Soil | 89% | 95% |
| Rocky Terrain | 85% | 93% |

The fused system consistently outperformed individual modalities. For example, in rocky terrain, seismic sensors alone missed about 15% of light vehicles, while acoustic + magnetic fusion increased POD to above 90%.

#### 5.1.2 False Alarm

False alarms remain a key concern in vehicle detection, particularly due to wind (affecting acoustics), background ground vibrations (affecting seismic), and local ferrous clutter (affecting magnetics). Standalone magnetic sensing flagged many false positives near buried metallic debris. With fusion, FAR was reduced by ~50% compared to individual modalities.

- Acoustic channel: prone to wind/animal noise.
- Seismic channel: sensitive to human footsteps or nearby construction.
- Magnetic channel: highly triggered by metallic clutter.

By integrating all three, the system established consistent classification zones, reducing false triggers.

### 5.2 Qualitative Evaluation of Sensor Interactions

#### 5.2.1 Synergy Between Modalities

Several trial cases illustrated how weaknesses of one modality were compensated by others:

- Light vehicles: weak seismic signals in rocky terrain were supported by acoustic harmonics and confirmed by magnetic anomalies.
- Heavy tracked vehicles: strong seismic amplitude provided long-range detection, while acoustic harmonics aided classification, and magnetic sensors confirmed ferrous content.
- Cluttered zones: seismic sensors were triggered by human activity, but absence of magnetic disturbance and acoustic signature prevented false classification.

#### 5.2.2 Operator Confidence and Feedback

Operators reported greater confidence in fused system output since the classification probabilities were displayed as percentages (e.g., *"Truck – 94%"*). This reduced hesitation compared to traditional single-sensor alarms, where every alert appeared equally urgent. As a result, monitoring efficiency improved by ~15–20% during continuous trials.

### 5.3 Limitations and Challenges

1. **Environmental Variability:**
   - Heavy rain dampened seismic wave propagation, reducing effective detection range.
   - Strong winds degraded acoustic performance by ~10–12%.
   - Magnetic sensors showed drift in highly mineralized soils.
2. **System Complexity:**
   - The integrated node with three sensors, ADC, and wireless unit weighed more than standalone geophones, which could limit large-scale deployments.
   - Power consumption increased, requiring battery management strategies.
3. **Training Data Limitations:**
   - Current fusion algorithms were trained on limited vehicle datasets. New vehicle types (e.g., hybrid/electric with reduced acoustic signature) presented challenges.
   - Terrain-specific calibration was required to maintain accuracy.

### 5.4 . Role of the System in Operations

The integrated system provides multiple operational benefits:

1. Defense: Detects and classifies approaching vehicles in border or combat zones, giving early warning.
2. Transportation: Tracks vehicle flows on highways and urban roads, aiding smart traffic control.
3. Disaster Response: Identifies movement of rescue and emergency vehicles in disrupted communication zones.
4. IoT/UAV Integration: Can be embedded into UAVs or IoT platforms for wide-area monitoring.
   In all cases, fusion-based detection reduces false alarms, increases detection range, and provides confidence values to operators, making decision-making more reliable.

### 5.5 Functional Requirements of Vehicle Detection System

1. Terrain Adaptability: Sensors must operate reliably in diverse conditions (soft soil, rocky terrain, urban environments).
2. Robust Detection: Ability to detect both heavy tracked vehicles and lighter wheeled vehicles.
3. Noise Immunity: Acoustic and seismic channels must be resilient against environmental noise such as rain, wind, or human activity.
4. Power Efficiency: Wireless nodes should be energy-efficient for long-duration deployments.
5. Scalable Networking: The system must support multiple nodes working in coordination for wide-area coverage.
6. User Interface: Outputs should be presented as clear confidence levels (e.g., “Truck – 94%”) to reduce operator stress.

### 5.6 Limitations and Challenges

1. Environmental Variability: Rain dampened seismic signals; wind degraded acoustic accuracy by 10–12%; mineralized soils destabilized magnetic readings.
2. System Complexity: The prototype was heavier and more power-hungry than single-sensor systems.
3. Training Data Gaps: Limited datasets reduced accuracy for electric/hybrid vehicles with weaker acoustic signatures.

## 6. Conclusion

The integrated acoustic–seismic–magnetic vehicle detection system significantly improves detection accuracy and reliability compared to standalone sensors. Fusion achieves POD >95% and halves false alarms, ensuring robust detection in diverse terrains. This work demonstrates the feasibility of tri-modal sensor fusion for defense, transportation, and disaster management applications.

**7\6.1 Future Work**

Future developments will focus on:

1. Robotic Integration: Mounting sensor arrays on autonomous ground robots or UAVs for mobile detection.
2. Machine Learning Models: Deep learning for classification of diverse vehicle types including electric vehicles.
3. Large-Scale Deployment: Optimizing wireless networking for city-wide or border-wide sensor grids.
4. Real-World Trials: Expanding validation datasets across terrains, climates, and vehicle classes.

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