A CLOUD-BASED KALMAN FILTER APPROACH FOR NOISE REDUCTION IN DIAGNOSTIC TROUBLE CODES (DTCS)

by

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To my mother and father – your love is my greatest blessing. Your sacrifices lit the path that brought me here. Every late night, every dream I chased, every challenge I overcame, I carried your strength with me

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PREFACE

This dissertation represents the culmination of years of academic study, professional experience, and personal dedication. The journey to this point has been shaped by passion for advancing technology, improving safety, and contributing meaningful solution to the challenges facing modern mobility and connected vehicle systems.

The work presented here reflects not only rigorous research, but also the insights gained from my time in automative industry, where real-world problems, customer needs, and technological limitations intersect. My goal throughout this research has been to bridge theory with practice and develop innovative approaches that can be applied in the field to improve safety, reliability, and customer experience.

This dissertation is also the result of countless late nights, continuous learning, and persistent determination. It required balancing professional responsibilities, academic requirements, and family life. Each contributing uniquely to the final outcome. This experience strengthened my belief in perseverance, long-term commitment, and the importance of pursuing knowledge with purpose.

Completing this work would not have been possible without the encouragement and support of my family, mentors, and colleagues who stood beside me throughout this

journey. Their presence provided the motivation to keep progressing, even in moments of challenge.

I hope that the contribution made through this research will support future innovations in connected vehicle safety and inspire others who are driven to make a meaningful impact in their fields.

Yamen Jawdat Taleb

ABSTRACT

A CLOUD-BASED KALMAN FILTER APPROACH FOR NOISE REDUCTION IN DIAGNOSTIC TROUBLE CODES (DTCS)

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This dissertation presents a cloud-based Kalman filter framework designed to reduce noise in diagnostic trouble code (DTC) signals and improve First Notice of Loss (FNOL) accuracy within connected vehicle systems. Modern vehicles generate extensive CAN-based diagnostic and sensor data, yet these signals are often influenced by noise, transient disturbances, and low-severity impacts that can trigger false DTC activations and unnecessary FNOL alerts. These inaccuracies create operational inefficiencies for automative OEMs and contribute to increased claim volumes, higher warranty expenses, and inconsistent assessments for insurance partners.

To address these challenges, this research develops and evaluates a Kalman filter-based noise reduction model executed in the cloud. Using CAN signal files collected from real vehicles testing, the model estimations the true underlying diagnostic state by filtering out random fluctuations, road disturbances, and non-critical impact signatures. The framework also incorporates a smart contract mechanism that securely timestamps

validated FNOL events, ensuring trusted, tamper-resistant data exchange between OEM and insurance companies.

Validation is conduction using CAN logs, simulated DTC fault scenarios, and synthetic impact profiles. Results demonstrate that the proposed model significantly reduce false-positive FNOL detection and accurately differentiates true collision events from low-impact disturbances. The integration of smart contracts provides an automated and verifiable method for sharing incident data with insurers, enabling faster claim triage, reduced fraud risk, and more precise repair cost estimation.

This work offers a scalable, cloud driven methodology that enhances vehicle diagnostic reliability, improves FNOL accuracy and strengthens collaboration between OEMs and insurance companies. The framework lays the foundation for a more secure, transparent, and data-driven ecosystem in modern mobility.

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LIST OF ABBREVIATIONS

Δv	change in vehicle velocity during impact
CAN	Controller Area Network
DTC	Diagnostic Trouble Code
EKF	Extended Kalman Filter
FNOL	First Notice of Loss
GPS	Global Positioning System
IMU	Inertial Measurement Unit
KF	Kalman Filter
SAE	Society of Automotive Engineers
VIN	Vehicle Identification Number
TPMS	Tire Pressure Monitoring System

CHAPTER ONE

INTRODUCTION

1.1 Background and Motivation

Modern vehicles operate as distributed cyber-physical systems composed of Electronic Control Units (ECUs) interconnected via Controller Area Network (CAN) communication buses that enable real-time monitoring, diagnostics, and event detection [1], [2]. Standardized diagnostic frameworks such as ISO 14229 Unified Diagnostic Services (UDS) and SAE J1979 define structured mechanisms for Diagnostic Trouble Code (DTC) generation, fault memory storage, and event reporting [3], [4]. In commercial and heavy-duty vehicle platforms, SAE J1939 further governs high-speed networked communication across distributed modules [5].

As vehicle connectivity has expanded, cloud-integrated diagnostic ecosystems have emerged to support fleet-level monitoring and enhanced event analytics [6], [7]. These architectures enable offboard processing of vehicle telemetry, thereby overcoming computational and memory constraints inherent in embedded ECUs [8]. However, the effectiveness of such systems remains highly dependent on the integrity of raw sensor signals collected from production vehicles.

Acceleration and inertial signals transmitted over CAN buses are inherently influenced by structural vibration, road irregularities, sensor bias drift, and stochastic measurement noise [9], [10]. Road-induced disturbances such as potholes, curb strikes, and suspension oscillations introduce transient signal spikes that may resemble collision signatures [11].

When processed using threshold-based logic, such disturbances can propagate through diagnostic decision layers and result in unintended DTC activations or false First Notice of Loss (FNOL) notifications [12], [13].

Conventional crash detection algorithms—including airbag sensing logic and Event Data Recorder (EDR) systems—rely primarily on calibrated acceleration thresholds and delta-V estimation within fixed time windows [14], [15]. While computationally efficient and suitable for real-time ECU execution, amplitude-based detection methods are sensitive to transient disturbances and platform-dependent calibration variability [16]. Telematics-based crash detection research has shown that false positive rates can increase significantly when noisy or ambiguous signals are processed without dynamic consistency validation [17].

Model-based diagnostic approaches provide an alternative to purely threshold-driven logic. State-space estimation techniques, particularly the Kalman filter introduced by Kalman in 1960 [18], offer an optimal recursive solution for estimating system states in the presence of Gaussian noise. Kalman filtering has been widely applied in navigation systems, robotics, aerospace guidance, and multi-sensor fusion applications [19], [20], where it enables reconstruction of physically consistent system states from corrupted measurements.

Automotive applications of Kalman filtering have demonstrated effectiveness in vehicle dynamics estimation, suspension modeling, and inertial measurement fusion [10], [21]. However, the structured integration of cloud-executed Kalman filtering for improving

FNOL classification and DTC stabilization using production CAN telemetry remains underexplored.

The emergence of scalable cloud computing infrastructures capable of executing recursive estimation algorithms beyond ECU constraints [7], [22] provides an opportunity to improve diagnostic reliability through advanced signal reconstruction techniques.

Therefore, this research is motivated by the need to reduce false DTC activations, enhance FNOL classification reliability, and improve crash detection robustness using a cloud-executed state-space filtering framework applied to real-world production CAN datasets.

1.2 Problem Definition

Despite advances in vehicle connectivity and diagnostic standardization, production crash detection systems face persistent challenges in noisy operating environments.

First, amplitude-based threshold detection methods are inherently sensitive to transient disturbances [16], [17]. Structural vibrations, road shocks, and sensor variability may produce acceleration peaks that exceed predefined thresholds without corresponding to meaningful vehicle momentum transfer.

Second, conventional diagnostic logic lacks dynamic consistency validation. While collision events follow impulse-momentum relationships consistent with vehicle dynamics theory [9], threshold-based detection does not verify whether observed signals correspond to sustained deceleration profiles expected in genuine impacts.

Third, embedded ECU architectures impose strict computational and memory limitations that constrain the implementation of advanced recursive estimation algorithms onboard [8]. As a result, many production systems rely on simplified decision rules rather than probabilistic state estimation techniques.

These limitations contribute to elevated false positive rates in FNOL classification. As demonstrated experimentally in Chapter 5, a baseline threshold-based detection model exhibited a false positive rate of 21.1% across 214 evaluated vehicle events.

Therefore, the central research problem addressed in this dissertation is:

How can cloud-executed state-space estimation improve crash detection reliability and reduce false FNOL notifications in noisy production CAN telemetry?

1.3 Research Objectives

The primary objective of this dissertation is to develop and experimentally validate a cloud-based Kalman filtering framework that improves diagnostic stability and FNOL event classification using production vehicle CAN signals.

The specific objectives are:

1. To statistically characterize noise and disturbance behavior in production CAN telemetry.
2. To formulate a discrete-time state-space vehicle motion model suitable for cloud execution.
3. To derive and implement a Kalman filtering architecture for signal reconstruction.
4. To develop innovation-residual-based validation logic for distinguishing collision impulses from transient disturbances.
5. To design an experimental evaluation framework using labeled real-world vehicle datasets.
6. To quantify improvements in classification accuracy, sensitivity, specificity, and false positive rate.
7. To evaluate computational feasibility for cloud-based deployment.

1.4 Research Questions

This dissertation investigates the following research questions:

1. How accurately can cloud-executed Kalman filtering reconstruct true vehicle motion states from noisy CAN telemetry?
2. To what extent does Kalman-based estimation reduce false DTC activations compared to threshold-based detection?

3. How reliably can innovation-residual monitoring differentiate true collision events from transient disturbances?
4. What quantitative improvements in FNOL classification performance are achieved using the proposed framework?
5. Is cloud-based execution computationally feasible for fleet-scale diagnostic enhancement?
6. What measurable operational impact results from reduced false FNOL notifications?

1.5 Scope of Research

Included Scope

This research includes:

- Analysis of production CAN telemetry from controlled vehicle testing.
- Statistical modeling of acceleration noise behavior.
- Development of discrete-time state-space filtering models.
- Cloud-based implementation of Kalman filtering.
- Innovation-residual-based FNOL classification logic.
- Experimental performance comparison between filtered and unfiltered signals.
- Statistical evaluation using confusion matrices and performance metrics.

Out of Scope / Limitations

This research does not include:

- Deployment within production ECUs.
- Machine-learning-based classification models.
- Full insurance workflow integration.
- Large-scale fleet validation beyond available datasets.
- Evaluation of all crash typologies.

1.6 Contributions of the Dissertation

This dissertation makes the following experimentally validated contributions:

1. A cloud-executed state-space filtering architecture for production CAN telemetry.
2. A quantified reduction in false positive rate from 21.1% to 5.3%, increasing overall classification accuracy from 84.6% to 95.3% across 214 evaluated events.
3. An innovation-residual-based FNOL validation strategy for distinguishing transient disturbances from sustained impacts.
4. A structured experimental evaluation methodology using real-world vehicle datasets.
5. Demonstration of computational feasibility for cloud-based diagnostic enhancement.

1.7 Dissertation Organization

- Chapter 1 introduces motivation, problem definition, objectives, scope, and contributions.
- Chapter 2 reviews related work in vehicle diagnostics, CAN signal noise modeling, crash detection methodologies, and state estimation theory.
- Chapter 3 presents the proposed methodology and state-space formulation.
- Chapter 4 describes the cloud-based implementation and filtering framework.
- Chapter 5 presents experimental results and statistical performance evaluation.
- Chapter 6 provides case studies demonstrating practical applicability.
- Chapter 7 concludes the dissertation and outlines future research directions.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter reviews prior work relevant to vehicle diagnostics, CAN signal behavior, Diagnostic Trouble Codes (DTCs), First Notice of Loss (FNOL) detection, Kalman filtering, cloud-based processing architectures, and blockchain-enabled smart contracts. The purpose of this review is to establish the technical foundation for the proposed methodology and identify gaps that this dissertation aims to address.

2.2 Vehicle Diagnostics and OBD Systems

Modern vehicles rely on onboard diagnostic (OBD) systems to identify malfunctions and support service procedures. Diagnostic Trouble Codes (DTCs) serve as indicators of abnormal conditions detected by sensors or ECUs [2]. The accuracy of DTCs depends on threshold logic embedded within ECUs, which analyze sensor inputs for patterns consistent with failure modes.

Prior research has shown that diagnostic reliability is heavily influenced by signal quality, calibration parameters, and fault classification logic [5]. Despite advancements in diagnostic frameworks, false positives remain a significant challenge due to noisy or unstable sensor data.

2.3 CAN Bus and Signal Characteristics

Modern in-vehicle electronic systems rely on the Controller Area Network (CAN) to exchange diagnostic and operational information among Electronic Control Units (ECUs). CAN is a message-based, broadcast bus designed to be robust to electrical disturbances through arbitration, cyclic redundancy check (CRC), frame checks, and error handling mechanisms defined at the physical and data-link layers [28]. These protocol mechanisms improve communication reliability, but they do not eliminate measurement uncertainty originating upstream at the sensor and signal-conditioning stages.

From a diagnostics perspective, many Diagnostic Trouble Codes (DTCs) are triggered by decision logic operating on thresholded sensor signals (e.g., acceleration, rotational speed, voltage, pressure, temperature) sampled and communicated over the CAN bus. As a result, the quality of CAN-carried signals is influenced not only by network integrity, but also by real-world driving conditions that introduce disturbances into the underlying measurements. Examples include road roughness and pothole events that induce short-duration vibration spikes, curb strikes that resemble impact pulses, component aging that shifts sensor bias, and electromagnetic interference that perturbs analog front ends prior to digitization and message transmission [29], [30]. In field operation, these effects can lead to transient excursions that satisfy diagnostic thresholds even in the absence of a true fault, increasing the probability of spurious DTC activations and inconsistent diagnostic conclusions.

In addition, the in-vehicle environment is inherently variable: payload, speed, suspension characteristics, and surface type change the vibration spectrum and transient dynamics observed by onboard sensors. This variability complicates the design of fixed thresholds that are valid across drivers, vehicle platforms, and operating contexts [29]. Consequently, noise and disturbances can propagate through diagnostic logic and appear as false positives (fault asserted without a fault) or unstable fault toggling (fault asserted intermittently), motivating the need for systematic noise-reduction and signal-stabilization methods before final diagnostic classification [30].

2.4 Kalman filtering for automative signal stabilization and state estimation

Kalman filtering provides a principled framework for estimating the underlying state of a dynamic system from noisy measurements. In its classical form, the Kalman filter assumes linear system dynamics with Gaussian process and measurement noise and computes an optimal minimum-variance estimate recursively over time [31]. This recursive structure is well suited to automotive systems because signals are streamed continuously and must be interpreted in real time or near-real time, often with limited latency budgets.

Automotive sensing and diagnostics frequently involve multi-source signals (e.g., accelerometers, wheel speeds, yaw rate sensors) whose measurements contain noise, bias drift, and transient disturbances. In such settings, Kalman-based estimators can reduce apparent variability by combining a physics-based prediction model with measurement updates, thereby suppressing random noise while preserving meaningful transient behavior. Extensions such as the Extended Kalman Filter (EKF) support nonlinear models commonly encountered in vehicle dynamics and have been widely evaluated for vehicle state estimation problems including tire/road force and sideslip-related states, demonstrating practical benefits when measurements are noisy and operating conditions change over time [32], [33].

For diagnostic applications, the value of a Kalman filtering approach is twofold. First, it improves signal stability, which reduces the chance that momentary spikes (caused by vibration or electrical disturbances) trigger a diagnostic threshold. Second, it supports consistent interpretation by producing a smoothed estimate aligned with expected system dynamics, which can reduce oscillatory fault behavior and improve repeatability of DTC decisions across comparable driving conditions. These properties motivate the cloud-based Kalman filtering strategy developed in this dissertation to stabilize diagnostic and event-detection signals prior to classification.

2.5 Prior Work on Collision/FNOL Event Detection and False Alert Drivers

Automated collision detection and First Notice of Loss (FNOL) event identification depend on reliably distinguishing true crash events from non-crash disturbances that can produce similar short-duration signatures. A common baseline approach is threshold detection on impact-related features such as acceleration magnitude, directional impulse characteristics, or proxy measures correlated with crash severity. While thresholds are simple and computationally efficient, prior work has shown that real-world driving can produce crash-like transients (e.g., potholes, curb impacts, rough-road vibration), which increases the risk of false positives when thresholds are set aggressively [29], [34].

In the broader literature on automated crash detection, smartphone- and vehicle-sensor-based systems highlight the challenge of separating true crashes from benign high-acceleration events. For example, Wreck Watch demonstrated automated accident detection and notification using mobile sensing, and explicitly reported the practical difficulty of avoiding false alarms in the presence of non-crash shocks and driving variability [34]. These findings are directly relevant to FNOL workflows because false FNOL alerts create operational inefficiencies (unnecessary escalations, claim triage overhead), reduce customer trust, and can lead to noisy event datasets that degrade downstream analytics.

Therefore, prior research motivates a filtering-and-classification pipeline where raw sensor measurements are first stabilized (to reduce sensitivity to short-duration noise spikes) and then interpreted using features that better capture true crash dynamics. In this dissertation, the proposed cloud-based Kalman filter stage targets the upstream disturbance problem—road-induced transients and measurement noise—so that subsequent FNOL classification can improve detection reliability while reducing false positive activations.

2.6 Innovation based Residual monitoring and statistical fault validation

In addition to state estimation, Kalman filtering provides a structured framework for residual generation through the innovation sequence. The innovation, defined as the difference between the predicted measurement and the actual measurement, serves as a statistically meaningful indicator of model consistency [35]. Under standard Kalman assumptions, the innovation sequence is a zero-mean Gaussian process with covariance determined by the system and measurement noise parameters [31].

Residual-based fault detection has been widely studied in control and diagnostic systems. Basseville and Nikiforov [23] established that abrupt change detection can be achieved by monitoring statistical deviations in residual sequences. Similarly, Gertler [24] demonstrated that residual evaluation enables analytical redundancy, allowing detection of inconsistencies between modeled system dynamics and observed measurements.

In automotive applications, observer-based residual generation has been used to identify sensor faults, actuator malfunctions, and parameter deviations [25], [27]. Residual monitoring frameworks typically employ statistical hypothesis testing, including chi-square tests and normalized innovation squared (NIS) metrics, to determine whether measurement deviations exceed expected stochastic bounds [36], [37]. These statistical techniques provide a probabilistic alternative to deterministic amplitude thresholds.

The advantage of innovation-based validation lies in its dynamic consistency verification. Rather than reacting to instantaneous amplitude exceedance, residual monitoring evaluates whether deviations persist relative to the predicted system trajectory. This distinction is critical in automotive crash and disturbance detection scenarios, where short-duration spikes may occur due to road irregularities but do not reflect sustained momentum transfer or collision dynamics.

Recent studies in model-based fault diagnosis have emphasized that combining state estimation with residual-based decision logic improves robustness against noise and transient disturbances [38]. In particular, residual evaluation reduces sensitivity to high-frequency measurement noise while preserving responsiveness to genuine structural changes in system behavior.

Despite extensive literature on residual-based detection in control systems and industrial diagnostics, its structured application to cloud-executed FNOL validation using production CAN telemetry remains limited. Most prior implementations are embedded within ECU observers or laboratory validation frameworks rather than deployed within scalable offboard processing architectures.

Therefore, integrating innovation-based residual monitoring into a cloud-based Kalman filtering pipeline represents a logical extension of established fault detection theory into connected vehicle diagnostic ecosystems. This integration enables statistical validation of impact-related signals prior to final FNOL classification, potentially reducing false positive activations caused by transient disturbances.

2.7 Cloud based processing in connected vehicle systems

The rapid evolution of connected vehicle technologies has enabled the transmission of high-frequency telematics data from production vehicles to offboard cloud infrastructure. Modern vehicles equipped with telematics control units (TCUs) continuously transmit Controller Area Network (CAN) signals, diagnostic events, and vehicle health indicators to centralized servers for remote monitoring and analytics [39]. This shift from purely embedded processing to hybrid edge-cloud architectures introduces new opportunities for advanced signal reconstruction and statistical analysis.

Traditional embedded diagnostic systems are constrained by real-time computational limits, memory availability, and deterministic execution requirements [8]. As a result, onboard Electronic Control Units (ECUs) typically rely on threshold-based logic and simplified filtering mechanisms. While suitable for real-time safety-critical decisions, these embedded constraints limit the implementation of more computationally intensive probabilistic estimation methods, such as multi-signal Kalman filtering or innovation covariance evaluation.

Cloud computing platforms provide scalable processing power, distributed storage, and flexible algorithm deployment capabilities that exceed embedded ECU limitations [40]. Shi et al. [7] described the evolution of edge-to-cloud computing frameworks for Internet of Things (IoT) applications, emphasizing that complex analytics tasks can be shifted to centralized infrastructure where computational scalability is not constrained by vehicle hardware. In vehicular networks, Alam et al. [22] further demonstrated that cloud-based vehicular systems enable large-scale data aggregation and post-processing that are impractical within in-vehicle systems.

From a telematics perspective, cloud architectures allow:

- Long-window signal reconstruction
- Cross-signal correlation analysis
- Statistical modeling over fleet-level datasets
- Iterative algorithm refinement without vehicle firmware updates

These capabilities are particularly relevant for crash and FNOL validation systems, where false positive reduction requires dynamic consistency verification across multiple signals rather than isolated threshold triggers.

Several studies have investigated cloud-assisted vehicle diagnostics. Di Natale et al. [30] emphasized that CAN telemetry, when aggregated offboard, can support advanced anomaly detection beyond onboard capabilities. More recently, research in cloud-based fleet analytics has shown that centralized signal processing improves diagnostic classification stability when compared to local-only implementations [41].

However, the majority of prior work in connected vehicle cloud analytics has focused on fleet monitoring, predictive maintenance, or usage-based insurance modeling [16], rather than probabilistic reconstruction of impact-related motion signals using state-space estimation.

Furthermore, crash detection systems implemented in smartphones or embedded modules have typically relied on raw acceleration thresholds or heuristic pattern recognition [34]. These systems do not incorporate dynamic state estimation to validate motion continuity prior to event classification.

Consequently, there exists a research gap between:

- Embedded threshold-based crash detection
- Fleet-level telematics analytics
- Probabilistic state-space reconstruction for FNOL stabilization

The integration of cloud-based Kalman filtering with innovation-driven decision logic represents a novel architectural approach that leverages scalable computation to improve diagnostic stability in production vehicles.

2.8 Research Gap and Chapter summary

The literature reviewed in this chapter establishes that vehicle diagnostics, crash detection, and state estimation have each been extensively studied within their respective domains. On-board diagnostic systems rely on standardized fault detection mechanisms [3], [4], while model-based diagnostic theory provides analytical frameworks for residual generation and fault isolation [15], [24], [38]. Controller Area Network (CAN) telemetry has been characterized in terms of noise susceptibility and signal disturbance propagation [28], [29], and vehicle dynamic modeling principles are well documented in classical automotive engineering literature [9], [10].

Crash detection systems implemented in embedded airbag controllers and smartphone-based sensing platforms primarily utilize threshold-based logic and heuristic pattern recognition [12], [13], [34]. While these systems perform effectively for high-severity structural impacts, they are sensitive to noise, vibration, and transient disturbances. As discussed in Sections 2.3 and 2.4, transient acceleration spikes generated by road irregularities, curb strikes, or braking events may resemble impact signatures when evaluated using amplitude-only logic.

Kalman filtering and state-space estimation techniques offer mathematically rigorous approaches to reconstructing system dynamics in the presence of noise [18], [20], [31]. Innovation-based residual monitoring further provides statistically grounded methods for evaluating consistency between predicted and observed measurements [23], [35], [37]. These techniques have been widely applied in aerospace navigation, industrial control systems, and automotive observer-based fault detection [25], [32]. However, the majority of automotive applications focus on embedded observers for parameter estimation or stability control rather than FNOL stabilization or crash validation using production telematics data.

Furthermore, although cloud-based vehicular analytics platforms enable large-scale data aggregation and fleet-level processing [22], [39], [40], their primary focus has been predictive maintenance, usage-based insurance modeling, and traffic management rather than probabilistic motion reconstruction for crash validation. Existing telematics-driven insurance frameworks typically analyze summary statistics or event triggers rather than reconstructing continuous vehicle motion using state-space filtering prior to FNOL decision logic [16].

Therefore, a clear gap emerges at the intersection of:

• Production CAN telemetry

• State-space motion reconstruction

• Innovation-based statistical validation

• Cloud-executed scalable processing

• FNOL classification stabilization

To date, no structured framework has been presented that integrates cloud-based Kalman filtering with innovation monitoring to stabilize diagnostic signals and reduce false positive FNOL activations in production vehicle environments.

This dissertation addresses that gap by proposing:

1. A cloud-executed state-space vehicle motion model derived from production CAN signals.
2. A Kalman filtering framework for noise reduction and motion reconstruction.
3. An innovation-driven statistical validation mechanism for event consistency.
4. An FNOL classification architecture that leverages reconstructed motion states rather than raw acceleration thresholds.

By combining estimation theory, residual monitoring, and scalable cloud processing, the proposed framework advances automotive diagnostic validation beyond embedded threshold logic and contributes to the development of more reliable connected vehicle safety ecosystems.

CHAPTER THREE

METHODOLOGY & CLOUD-BASED SYSTEM ARCHITECTURE

3.1 Problem Formulation

Connected vehicles continuously generate high-frequency inertial and kinematic telemetry data that can be leveraged for automated crash detection and insurance analytics [42], [43]. However, raw telematics signals are frequently corrupted by broadband stochastic noise, road-induced vibration, sensor bias drift, quantization effects, CAN-bus scheduling delays, and cellular packet jitter [44]–[46].

Acceleration measurements used for estimating velocity change (Δv) are particularly sensitive to these disturbances. When directly integrated without conditioning, accumulated noise produces unstable state estimates that degrade crash severity classification and First Notice of Loss (FNOL) reliability [47], [48].

From a signal-processing perspective, the fundamental challenge is to reconstruct a physically meaningful crash state from noisy measurements while maintaining statistical consistency and bounded estimation error [49], [50]. The problem can be formalized as a state-space estimation task in which:

- The vehicle crash state evolves according to nonlinear vehicle dynamics.
- Sensor observations are corrupted by Gaussian and non-Gaussian disturbances.

- Classification decisions must align with SAE J224 crash severity metrics [12].

Therefore, the objective is to design a cloud-based estimation framework capable of:

1. Conditioning noisy CAN-based acceleration signals
2. Estimating velocity change (Δv) robustly
3. Reducing false positives caused by vibration and road disturbances
4. Preserving sensitivity to true crash events

This formulation establishes the mathematical foundation for the Kalman-based filtering methodology presented in this chapter [18], [20], [31].

3.2 Rational for Cloud-Centric Processing

Embedded vehicle Electronic Control Units (ECUs) operate under strict computational, memory, and functional safety constraints (ISO 26262) [51]. These constraints limit the feasibility of adaptive filtering, covariance tuning, and multi-domain feature extraction directly on the vehicle platform [52].

While on-board threshold logic provides real-time detection capability, it lacks robustness to sensor noise variability, fleet-level calibration drift, and environmental uncertainty [17], [24].

Cloud-based execution enables:

- High-rate state estimation using adaptive covariance models
- Centralized parameter tuning across vehicle fleets
- Deterministic replay for insurance auditability
- Continuous algorithm refinement without vehicle software updates

Cloud computing architectures provide elastic compute resources and scalable data processing pipelines suitable for large-scale telematics analytics [40], [53].

From a control-theoretic standpoint, offloading estimation to the cloud enables implementation of computationally intensive filtering techniques such as Extended Kalman Filtering (EKF) and adaptive noise modeling [20], [36].

Therefore, in this research:

- All signal conditioning, state estimation, feature extraction, and FNOL decision logic are executed offboard in the cloud.
- The vehicle functions as a telemetry acquisition node.
- Estimation robustness and classification accuracy are enhanced through centralized algorithm management.

3.3 System Architecture Overview

The proposed cloud-centric architecture consists of four logical layers:

1. Vehicle Sensor Layer

High-frequency acceleration and CAN-based telemetry signals are acquired from embedded vehicle sensors and transmitted through the telematics control unit (TCU) [28], [30].

2. Cloud Signal Conditioning Layer

Incoming data streams undergo:

- Timestamp alignment
- Outlier rejection
- Bias correction
- Kalman-based state estimation

3. Feature Extraction Layer

From the filtered state estimates, the system derives:

- Velocity change (Δv)
- Peak acceleration
- Crash pulse duration
- Energy-related metrics

These features align with SAE crash severity characterization methodologies [12], [13].

4. Classification & FNOL Decision Layer

A rule-based classification framework evaluates crash severity and triggers FNOL events based on calibrated Δv thresholds.

False positives caused by road vibration are mitigated through:

- Temporal consistency checks
- Multi-sample threshold validation
- Statistical residual monitoring [37], [38]

The architecture ensures:

- Reduced false positive rate
- Maintained sensitivity to true crash events
- Improved FNOL stability compared to amplitude-threshold baselines

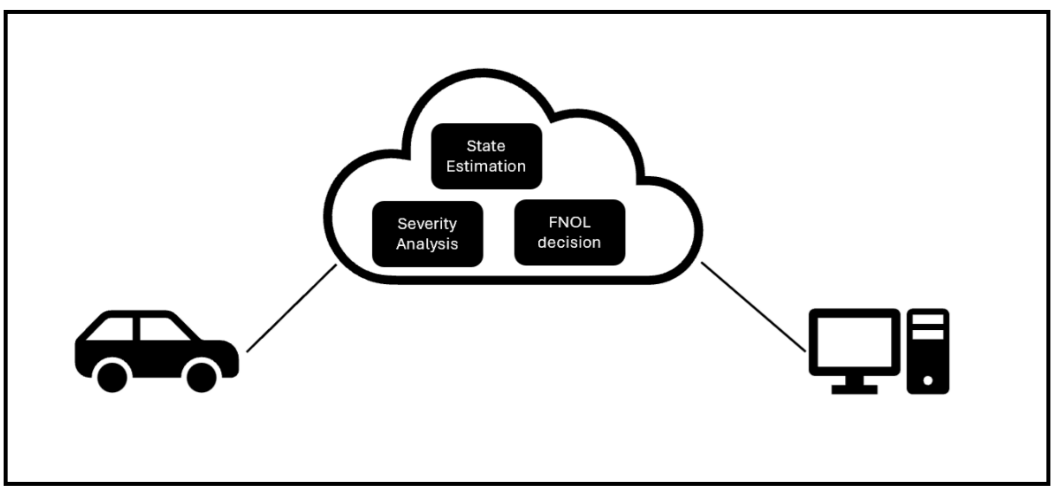

Figure 3.1 Cloud based connected vehicle diagnostic and insurance framework (CVDIF)

3.4 Vehicle Sensor Acquisition and Conditioning

Telematics data used in this study are acquired from production-grade automotive sensing systems, including tri-axial accelerometers, vehicle speed signals from the powertrain control module (PCM), wheel-speed sensors, and inertial measurements available over the Controller Area Network (CAN) bus [28], [30], [55].
Sampling rates range between 40–200 Hz depending on sensor type and vehicle configuration. These measurements are subject to asynchronous transmission, packet jitter, and quantization effects due to CAN scheduling and telematics buffering [44], [56].
To ensure numerical stability and temporal coherence prior to state estimation, incoming telemetry streams undergo structured cloud-based preprocessing:

Time Synchronization

Timestamp alignment is performed using interpolation and buffering techniques to correct cellular transmission jitter and asynchronous sampling artifacts [57].

Outlier Suppression

Transient spikes caused by potholes, curb strikes, and mechanical shocks are mitigated using robust statistical filtering methods, including median absolute deviation (MAD) and residual gating techniques [23], [58].

Missing Data Mitigation

Short-duration packet loss is addressed through Kalman smoothing and model-based interpolation to preserve temporal continuity [20], [36].

Signal Normalization

Measurements are normalized to bounded numerical ranges to prevent covariance divergence and numerical instability during recursive filtering [49].

These preprocessing operations ensure that subsequent state estimation operates on coherent, well-conditioned signals suitable for physically consistent motion reconstruction.

3.5 End-to-End Algorithmic flow

Figure 3.2 illustrates the deterministic processing pipeline from raw vehicle telemetry to FNOL decision output.

The architecture consists of five sequential stages:

1. Signal Acquisition – Raw inertial and vehicle signals are captured through embedded ECUs and transmitted via the telematics control unit (TCU).
2. Preprocessing & Conditioning – Timestamp correction, outlier suppression, and normalization are applied.
3. State Estimation – A cloud-based Kalman filter reconstructs vehicle motion states.
4. Feature Extraction – Crash-related physical metrics such as Δv, peak acceleration, and crash pulse duration are computed.
5. Severity Classification & FNOL Triggering – Threshold-based logic evaluates crash severity and generates FNOL events aligned with SAE standards [12].

The pipeline is deterministic in structure but probabilistic in estimation, ensuring repeatability while accounting for uncertainty propagation [31], [50].This structured separation between conditioning, estimation, and classification reduces false positive activation while preserving sensitivity to true crash events.

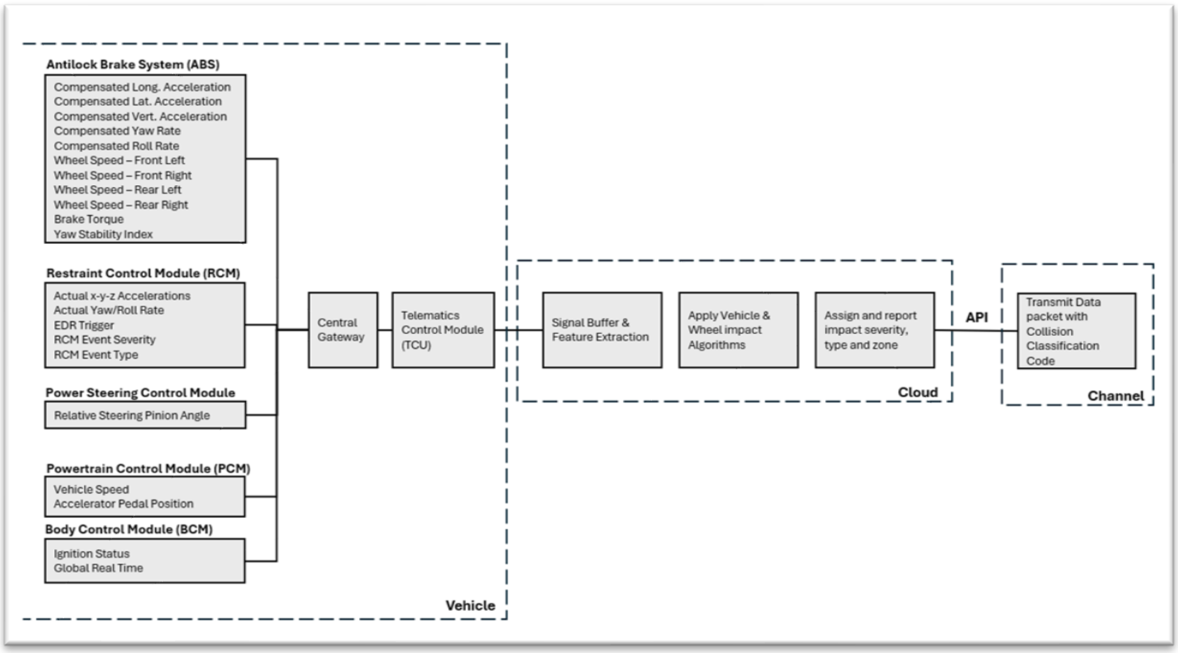

Figure 3.2 End-to-End Signal Flow

3.6 Cloud-Based Kalman Filter State Estimation

The objective of this section is to formally describe how noisy vehicle motion measurements are transformed into a statistically consistent and physically meaningful crash state estimate.

Prior to crash severity classification or FNOL decision-making, vehicle motion must be reconstructed in a manner robust to:

- Sensor noise
- Bias drift
- Quantization error
- Integration instability

The Kalman filter is adopted as the core estimation mechanism due to its optimality under Gaussian noise assumptions and its minimum mean-square error properties [18], [36], [50]. By recursively balancing model predictions against sensor observations, the Kalman filter produces statistically consistent state estimates even in the presence of significant noise and modeling uncertainty [35], [37]. The reconstructed motion state serves as the foundation for physics-based crash feature extraction described in Section 3.7.

3.6.1 Limitations of Raw Inertial Measurements

Inertial measurements obtained from production vehicle accelerometers are inherently noisy due to:

- Road-induced vibration
- Thermal drift

- Sensor bias
- Quantization noise
- Mounting misalignment

These error sources are well documented in automotive sensing literature [19], [31], [59].

When acceleration measurements are directly integrated to estimate velocity, noise accumulates over time, resulting in unbounded drift and physically implausible velocity estimates [21], [60]. During crash events, acceleration magnitudes increase sharply, and even small measurement errors can produce disproportionately large integration errors [47]. Consequently, direct numerical integration of raw acceleration signals is unsuitable for reliable crash-state reconstruction.

These limitations motivate the formulation of vehicle motion estimation as a probabilistic state estimation problem rather than a direct integration task.

3.6.2 Vehicle Motion Reconstruction as a State Estimation Problem

Rather than treating velocity as the time integral of acceleration, this work formulates vehicle motion reconstruction as a state estimation problem.

At each discrete time step k , the vehicle is represented by a state vector:

$$x_k = \begin{bmatrix} v_k \\ a_k \end{bmatrix}$$

Where:

v_k = vehicle velocity

a_k = longitudinal acceleration

The state evolves according to a linear discrete time model

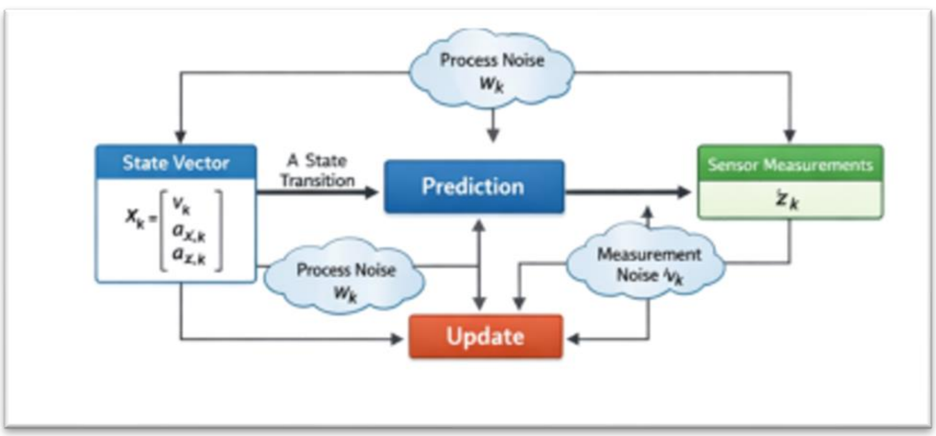

Figure 3.3 relationship between the state vector, motion model, sensor measurements and uncertainty propagation

This recursive framework:

- Bounds estimation error covariance
- Prevents integration drift
- Maintains statistical consistency
- Provides physically plausible crash stat reconstruction

Adaptive covariance tuning further improves robustness to vibration induced disturbances and modeling uncertainty [36][54]

3.6.3 Definition of the Vehicle Motion State

The vehicle motion state is defined as:

$\mathrm{x_k} =$ vkax,kay,k

$$x_k = \begin{bmatrix} v_k \\ a_{x,k} \\ a_{y,K} \\ a_{z,k} \end{bmatrix}$$

where $v_k$is longitudinal velocity and $a_{x,k}$ $a_{y,K}$ $a_{z,k}$ are tri-axial accelerations measured by the inertial measurement unit (IMU) along the longitudinal . lateral and vertical axes respectively.

This formulation is intentionally selected to estimate velocity and acceleration simultaneously, thereby avoiding the error amplification associated with direct numerical integration of acceleration. Similar state-space formulation are widely used in vehicle dynamics and inertial navigation literature [39[,[40].

The physical meaning, units and sources of each state variable are summarized in Table 3.1

Table 3.1 – Kalman Filter State and Measurement Definitions

Symbol	Description	Units	Physical Meaning
v_k	Longitudinal Vehicle Velocity	m/s	Forward vehicle motion
$a_{x,k}$	Longitudinal Acceleration	m/s^2	Braking /impact force
$a_{y,K}$	Lateral acceleration	m/s^2	Side impact / yaw motion
$a_{z,k}$	Vertical acceleration	m/s^2	Road /underbody response
z_k	Measurement vector	N/A	Noisy sensor observation
Q	Process noise covariance	N/A	Motion model uncertainty
R	Measurement noise covariance	N/A	Sensor uncertainty

3.6.4 Vehicle Motion Dynamics Model

Vehicle motion follows fundamental physical principles in which velocity evolves as function of acceleration. This relationship is expressed in continuous time as:

$$\dot{v}(t) = a_x(t)$$

Acceleration dynamics are modeled as a stochastic process to capture unobserved disturbances such as road excitation, structural vibration, and modeling uncertainty:

$$\dot{a}_i(t) = w_i(t) \ \ , i \in \{x, y, z\}$$

Where $w_i(t)$ represents xero-mean Gaussian process noise [36],[37].

After discretization with sampling interval Δt_1, the state evolution model becomes:

$$\mathrm{x_k = Ax_{k-1} + w_k}$$

3.6.5 Measurement Model and Sensor Uncertainty

Although the true vehicle motion state cannot be observed directly, noisy measurements are available from onboard sensors. These measurement are modeled as:

$$z_k = Hx_k + v_k$$

Where z_k represents measured velocity and acceleration signals and v_k represents measurement noise due to sensor imperfections.

This formulation allows the estimator to explicitly weight sensor information based on modeled uncertainty, rather than assuming all measurements are equally reliable. Such measurement models are standard in optimal filtering and vehicle state estimation theory [35],[36].

3.6.6 Prediction-Correction Mechanism

After each step, the Kalman filter performs two complementary operations:

1. Prediction, in which the current state estimate is propagated forward using the motion model
2. Correction, in which the predicted estimate is updated using new sensor measurements

The relative influence of the model and the measurements is governed by the Kalman gain, which is computed from the state covariance and measurement noise covariance. This mechanism allows the filter to suppress high-frequency noise while preserving the temporal structure of true crash dynamics.

3.6.7 Modeling and Propagation of Uncertainty

The Kalman filter explicitly tracks estimation uncertainty through the state covariance matrix. Two covariance matrices govern this behavior:

- Process noise covariance (Q), representing uncertainty in the motion model
- Measurement noise covariance (R), representing sensor uncertainty

Accurate specification of these matrices is essential for filter consistency. In this framework, covariance parameters are axis-specific and tuned in the cloud using innovation consistency tests, a widely accepted approach in optimal filtering [37],[38].

Cloud-based execution enables these parameters to e refined across large datasets, improving robustness across vehicle platforms and operating conditions.

3.6.8 Vehicle CAN signal Input

In practical automative deployment, the the inertial and vehicle motion signals used for crash interpretation are not obtained from laboratory instrumentation but from production vehicle CAN telemetry. These signals originate from multiple vehicle controllers including IMU/RCM, ABS, module, steering module, and powertrain controller, and are broadcast at 100 Hz.

The Kalman filter framework proposed in this dissertation is designed to operate on these production CAN signals, which include longitudinal, lateral, and vertical accelerations, yaw and roll rates, vehicle speed, wheel speeds, steering angle, accelerator position, and brake torque.

3.7 Crash Feature Extraction

Once the cloud-based Kalman filter reconstructs a stable and physically consistent estimate of vehicle motion (section 3.6), the remaining challenge is to determine whether that motion corresponds to a true structural crash and , if so, to quantify its severity in a manner suitable for insurance and emergency response. Raw motion estimates alone are insufficient. They must be interpreted through the lens of vehicle crash physics.

This section describes how reconstructed vehicle motion is translated into a compact set of physically interpretable crash features.

3.7.1 Establishing the Crash Event in Time

All crash-related features must describe the same physical event – typically 80-150 ms- during which the majority f momentum transfer and structural deformation occurs [23]. To ensure temporal consistency, a sliding window of 100-300 ms is applied to Kalman filtered signals, centered in the peak acceleration event. This window captures the complete rise and decay of the crash pulse while excluding unrelated pre-and post-event motion.

3.7.2 Momentum Change: Velocity Change (Δv)

The most fundamental indicator of a crash is a sudden change in vehicle momentum. This is quantified by the change in velocity:

$$\Delta v = v_{(t_2)} - v_{(t_1)}$$

Where t_1 and t_2 correspond to the boundaries of the crash window shown in figure 3.4 Δv is the primary metric used in SAE J224 crash severity classification and has a well-established correlation with injury risk, structural damage, and insurance loss magnitude

[23],[40]. In this framework, Δv is computed from Kalman-estimated velocity, rather than direct acceleration integration , significantly reducing drift and instability.

Δv answers the first and most critical questions:

- Did the vehicle experience a meaningful momentum change consistent with a crash?

3.7.3 Severity of Impact: Crash Pulse Intensity (Δv / Δt)

While Δv captures total momentum change, it does not describe how rapidly that change occurred. Two events may have similar Δv values but vastly different injury and damage outcomes depending on the duration of the impact.

Crash pulse intensity is therefore defines as:

$$\frac{\Delta v}{\Delta t}$$

This metric reflects the aggressiveness of the impact. Structural crashes typically produce large Δv values over very short durations, whereas non-crash disturbances (e.g., potholes) distribute motion over longer intervals.

The contrast between steep crash pulses and low-intensity disturbances is visually apparent in Figure 3.4

Crash pulse intensity answers the second question:

- How severe was the impact in terms of force application over time?

3.7.4 Force Magnitude and Direction: Peak Acceleration

The instantaneous forces acting on the vehicle during impact are reflected in peak acceleration:

$$a_{p_{ea}k} = \max\left(|a_x|, \left|a_y\right|, |a_z|\right)$$

Peak acceleration captures force magnitude, while the dominant axis provides insight into impact direction. Structural crashes typically produce high-magnitude acceleration along one or more dominant axes, whereas road disturbances often generate isolated vertical responses.

This feature complements momentum-based metrics by capturing instantaneous force characteristics and is summarized in Table 3.2

3.7.5 Structural Deformation Versus Transient Disturbance

High acceleration alone does not guarantee a structural crash. To distinguish sustained structural deformation from brief transient disturbances, signal energy and variance are computed over the crash window:

$$E = \sum_{i=1}^{N} a^2 i$$

$$\sigma^2 = \frac{1}{N}\sum_{i=1}^{N}(a_i - \bar{a})^2$$

Structural crashes generate sustained, multi-axis energy and elevated variance, whereas non-crash events typically produce short-duration, axis-specific spikes.

These distinctions are summarized in Table 3.2 and validated experimentally in Chapter 5.

This step answer the question:

- Was this event structurally significant or merely a transient disturbance?

3.7.6 Directional Coherence: Directional Consistency Index (DCI)

Beyond force magnitude, structural crashes exhibit consistent force direction due to rigid-body dynamics. This behavior is quantified using the Directional Consistency Index (DCI):

$$DCI = \frac{|corr| + 1}{3} c_0 r_1$$

High DCI values indicate correlated multi-axis motion consistent with a structural impact, while low values suggest random vibration or road excitation.

3.7.7 Structural Signature in the frequency Domain

Crash dynamics differ from road vibration not only in magnitude but also in frequency content. Structural crashes concentrate energy in low-frequency bands associated with vehicle body deformation, while road-induced vibration and sensor noise populate higher frequency bands.

This distinction is captured using the low-frequency energy ratio:

$$R_f = \frac{E_{0-10\ Hz}}{E_{20-200\ Hz}}$$

Structural crashes exhibit significantly higher low-frequency energy ratios than non-crash events. This behavior is summarized in Table 3.2

3.7.8 Feature Synthesis and Physical Coverage

Each extracted feature captures a distinct physical aspect of crash behavior:

- Δv – Momentum Change
- Δv / Δt – impact aggressiveness
- $Peak\ acceleration$ – force magnitude and direction
- $Enegry$ & $variance$ – structural deformation
- DCI – directional coherence
- $Frequency\ content$ – structural versus vibration signature

These features are consolidated in Table 3.2 , which maps mathematical definitions to physical interpretations.

Together, this feature set provides a non-redundant, physics-complete representation of crash dynamics, enabling robust severity classification and FNOL decision-making.

Table 3.2 – Crash features and physical interpretation

Feature	Formula	Physical meaning
Δv	$v_{(t_2)} - v_{(t_1)}$	Momentum change
Δv / Δt	-	Impact aggressiveness
Peak Acceleration	max |a|	Force magnitude
Energy	$\sum a^2$	Structural deformation

Variance	σ^2	Motion persistence
DCI	Correlation metric	Force directionality
FFT ratio	Low/high freq	Structural signature

While Table3.2 defines Δv as the change in velocity between two time instants, in real connected vehicle telemetry the velocity state cannot be obtained by direct integration of measured acceleration. Production IMU signals contains bias drift, quantization noise, and vibration induced disturbances that cause accumulated velocity error even during normal driving. As a result, a direct computation of $v(t_2) - v(t_1) = \int_{t_1}^{t_2} a_x(t)\,dt$ does not represent true vehicle momentum change. To ensure Δv reflects a physically meaningful quantity, this dissertation reconstructs vehicle motion using a Kalman filter state estimator prior to feature extraction. The estimator enforce dynamic consistency between acceleration and velocity states, allowing Δv to represent external energy transfer rather than sensor artifacts. Consequently, high frequency road disturbances produce negligible Δv, while structural collisions produce sustained velocity change corresponding to real impact severity.

3.7.9 Differentiation between Structural crashes and Road anomalies

Not all high-magnitude inertial events correspond to structural vehicle crashes. Road anomalies such as potholes, curb strikes, or debris impacts can generate sharp acceleration spikes without resulting in significant vehicle momentum change or structural deformation.

Figures 3.8 & 3.9 illustrate representative examples of wheel impact events captured during normal driving conditions. In both cases, tri-axial acceleration signals exhibit short-duration, high frequency spikes localized to individual wheels. However, vehicle velocity and wheel speed signals remain continuous, indicating negligible change in overall vehicle momentum.

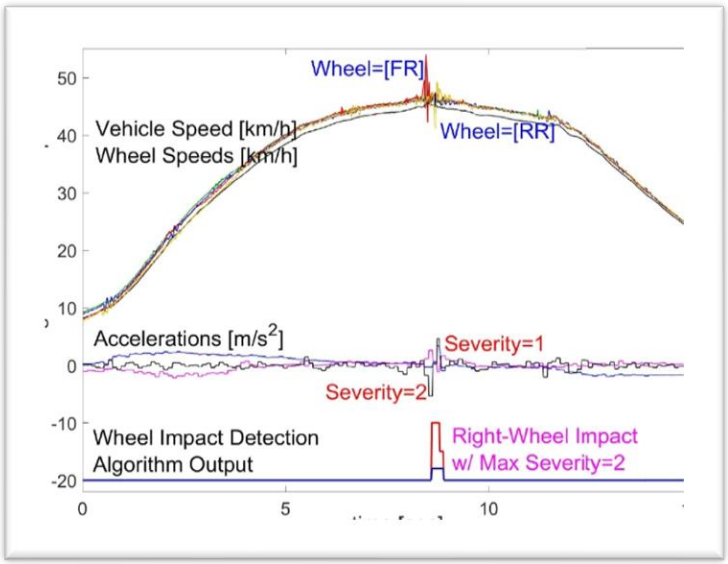

Figure 3.8 Pothole Impact

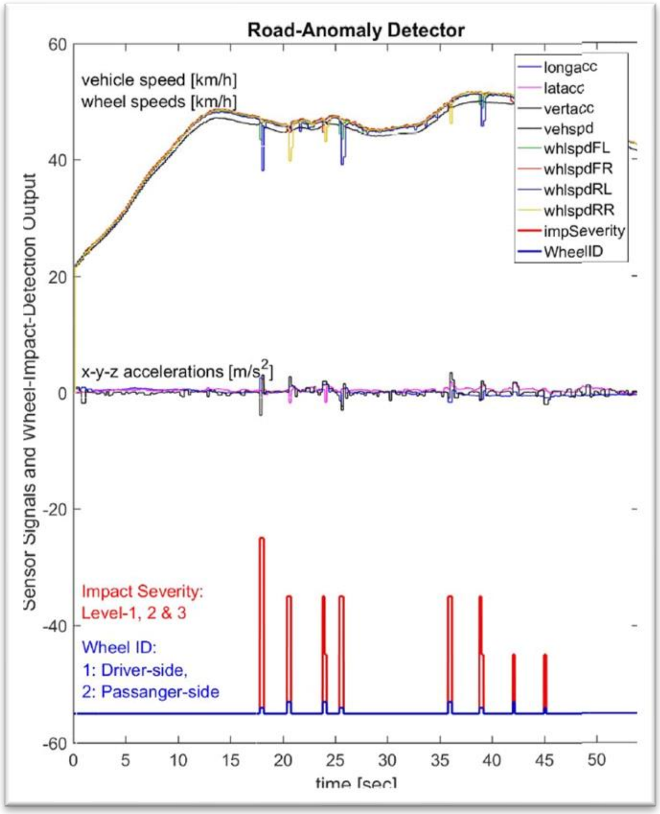

Figure 3.9 Road anomalies Detector

The extracted features reflect this physical behavior: velocity change (Δv) remains near zero, crash pulse duration is short, and signal energy is concentrated at higher frequencies. These characteristics distinguish road anomalies from structural crashes, which exhibit sustained acceleration pulse and measurable momentum loss.

by combining time-domain features, frequency-domain characteristics, and directional consistency, the proposed framework correctly classifies these vents as wheel impacts rather than collisions, thereby preventing false FNOL trigger while still enabling localized impact severity reporting.

3.8 FNOL Decision Logic and Severity Classification

The objective of this section is to describe how physics-grounded crash features extracted on section 3.7 are translated onto a reliable First Notification of Loss (FNOL) decision. While section 3,6 and 3.7 focus on reconstructing and interpreting vehicle motion, section 3.8 addresses the final and most consequential question:

- When should the system asset that a real crash has occurred and initiated insurance and emergency response work?

FNOL decision must balance competing risks, false positives generate unnecessary claims, operational cost, and loss of trust, while false negatives delay emergency response and increase safety risk. The section formulates FNOL triggering as a structured decision problem, rather than a simple threshold.

3.8.1 FNOL as a Decision Problem

In the context of connected vehicles and insurance systems, FNOL is fundamentallu a binary decision:

- FNOL Triggered – crash event reported
- FNOL Suppressed – event treated as non-crash

However, the consequences of incorrect decisions are asymmetric. False FNOLs create insurance leakage and customer dissatisfaction, while missed FNOLs pose safety and liability risks. Prior work has shown that threshold based system struggle to balance these tradeoffs under real world nose conditions [45].

Accordingly, FNOL triggering in this framework is formulated as a confidence-based decision, where multiples independent crash indicator are fused to estimate the likelihood of a true structural crash.

3.8.2 Inputs to the FNOL Decision Model

The FNOL decision model operates on the physics-grounded crash features extracted in section 3.7. these feature captured complementary aspects of crash behavior:

- Momentane change (Δv)
- Impact aggressiveness (Δv / Δt)
- Force magnitude and direction (peal acceleration, DCI)
- Structural deformation (energy and variance)
- Frequence signature (low-frequency FFT ratio)

Importantly, these features are computed from Kalman-estimated motion, ensuring that decision inputs are stable, physically consistent, and robust to noise.

3.8.3 Confidence Score Formulation

Rather than applying independent thresholds to individual features, this work defines an aggregated FNOL confidence score:

$c = \sum_{i=}^{N} \omega_i f_i$

Where:

- f_i Represents a normalized crash feature
- ω_i Represents the corresponding feature weight
- c Represents the overall confidence that the observed event is s structural crash

Feature normalization ensure that metrics with different units and scales contribute comparably to the decision. Feature weights reflect the relative importance of each physical phenomenon, with Δv and crash pulse intensity typically carrying higher weight due to their direct relation to injury risk and insurance severity [23],[40].

3.8.4 FNOL Triggering Criterion

An FNOL event is trigger when the confidence score exceeds a decision threshold :

$C > T_{FNOL}$

The threshold T_{FNOL} defines the operation point of the system and directly controls the tradeoff between false positive and false negatives. Selection of this threshold is therefore a critical design decision.

3.8.5 Severity Classification and SAR J224 Alignment

When FNOL event is triggered, crash severity is classified using SAE J224 Δv thresholds [23]. Δv serve as the primary severity metrics due to its strong correlation with injury risk and insurance loss magnitude.

Kalman filtering significantly improve Δv stability near severity boundaries, reducing misclassification between low, medium, and high-severity events. This improvement is quantified experimentally in Chapter 5.

By separating FNOL triggering from severity classification, the framework avoids conflating detection with crash severity, improving both interpretability and robustness.

CHAPTER FOUR

EXPERIMENTAL DESIGN AND VALIDATION METHODOLGY

4.1 Chapter overview and validation objectives

The objective of this chapter is to describe the experiment framework used to validated the cloud based Kalman filtering and first notification of loss (FNOL) decision architecture introduced in chapter 3 using real fleet crash test vehicles and fleet testing vehicles. While chapter 3 establishes the theoretical foundations and algorithmic design of the system, this chapter focuses on how those methods are evaluated under realistic operating conditions using real vehicle signals.

The validation strategy in this chapter is designed to answer three core questions:

1. Can Kalman filter reliably reconstruct vehicle motion in the presence of sensor noise?
2. Do extracted crash feature remain stable and physically meaningful under real sensor noise?
3. Can the FNOL logic distinguish structural crashes from non-crash disturbances observed in fleet vehicles?

4.2 Validation Philosophy

Rather than using synthetic or idealized signals, this work validated performance using naturally noisy inertial signals obtained from fleet vehicles. This ensures that sensor mounting effects, vibration, thermal variation, and electronics noise are inherently present in the evaluation.

The emphasis is on physical interpretability, not only numerical improvement.

4.3 Fleet Data Source

4.3.1 Fleet Crash Test vehicles

Controlled crash test vehicles provide:

- Tri-axial acceleration signals
- Known crash onset timing
- Impact severity

These signals serve as ground truth for crash behavior.

4.3.2 Fleet Driving Vehicles – Non crash events

Fleet vehicles in daily operation provide signals from:

- Pothole
- Curb strikes
- Rough road
- Aggressive maneuvers

These events generate acceleration spikes that resemble crash signatures and are critical for FNOL false-positive evaluation.

Table 4.1 – Fleet Validation Data

Source	Signals	Event Type	Purpose
Crash test vehicles	a_x, a_y, a_z	**Collision**	**Ground truth**
Fleet driving vehicles	a_x, a_y, a_z	**Road anomalies**	**False positive**

4.4 Natural Sensor Noise in Fleet Signals

Fleet vehicles signals inherently contains realistic noise due to:

- Vibration
- Mounting difference
- Electrical noise
- Environmental conditions

Because this nose is naturally present, no artificial noise injection is required.

4.5 Cloud-based Kalman filtering of Fleet data

All inertial data collected from fleet crash vehicles and fleet driving vehicles were processed in a cloud-based computational environment designed to emulate modern connected vehicle data architectures. Rather than executing signal processing within the vehicle, all Kalman filtering, feature extraction, and FNOL decision evaluation were performed off-board using centralized compute resources.

The datasets used for validation consist of production CAN telemetry captured at 100 Hz from fleet vehicles rather than high frequency laboratory IMU logs. This ensures that the validation environment reflects realistic connected vehicle conditions.

Fleet IMU signals were uploaded to a cloud storage repository where time-synchronized tri-axial acceleration data cloud be accessed for batch processing. The Kalman filter, crash feature extraction, and FNOL evaluation algorithms described in Chapter 3 were implanted using a python-based scientific computing environment.

The experimental workflow consisted of:

1. Importing raw IMU time-series data from fleet vehicles into the cloud environment.
2. Applying the Kalman filter to reconstruct motion states for each event window.
3. Computing crash features such as Δv, energy, pulse duration, and directional consistency.
4. Applying FNOL decision logic using the computing features.
5. Recording performance metrics including RMSE, feature variance, detection latency, and false positive rate.

This setup mirror real connected vehicle architecture where vehicle telemetry is transmitted to backend servers for post-event analysis, diagnostics, and customer facing digital services. By performing all processing in the cloud using python-tools, the experiments demonstrate that motion reconstruction and FNOL decision can be achieved without reliance on safety-critical in vehicle ECUs.

The cloud environment also enabled consistent parameter control, repeatable analysis across multiples vehicles , and scalable processing of large fleet datasets, ensuring reproducibility of results.

4.6 Validation of motion reconstruction

The first validation objective evaluates whether the Kalman filter can reconstruct vehicle motion form noisy fleet IMU signals.

Motion reconstruction accuracy is quantified using the Root Mean Square Error (RMSE):

RMSE $= \sqrt{\frac{1}{N}\sum_{k=1}^{N}(x_k - \hat{x}_k)\text{^}2}$

Where x_k is the raw measurement and $\hat{x}_k$is the filtered estimate

Crash severity is evaluated using velocity change (Δv):

$\Delta v = \int_{t_1}^{t_2} a_x(t)\,dt$

Where t_1, t_2 define the crash pulse window.

These metrics demonstrates that Kalman filtering is essential for recovering the true crash dynamics from noisy fleet signals. Without filtering, integration drift and vibration noise distort the crash pulse and lead to inaccurate Δv estimation, making feature extraction unreliable.

This section builds upon establish Kalman filtering research [57],[58] and extends prior work by the author on cloud based vehicle event analysis [59] and patented cloud assisted detection architecture [60]

4.7 Validation of crash feature stability

The stability of crash evaluated in this section is directly dependent on the Kalman filtering process described in section 4.6. without motion reconstruction, features such as velocity change, energy, and pulse duration vary significantly due to sensor noise and integration drift.

Following motion reconstruction using Kalman filter the next validation step evaluates whether the crash feature defined in section 3.7 remain physically meaningful and table when derived from real fleet IMU signals.

This step is critical because FNOL decisions are not based directly on filtered acceleration signals, but on features extracted from those signals. If these features are sensitive to sensor noise or vehicle variability, the FNOL logic will become unreliable even of motion reconstruction is accurate.

The crash features evaluated in this work include:

- Velocity change, representing total momentum change during the event

- Crash pulse duration, representing structural deformation time
- Signal energy, representing impact severity
- Directional consistency index (DCI), representing whether motion occurs along a consistent axis.

These features are chosen because they describe physical crash behavior rather than instantaneous signal magnitude.

To evaluate feature robustness , each feature is computed across multiples fleet crash events and fleet road anomaly events. The stability of each feature is measured using variance:

$$\sigma_f^2 = \frac{1}{m}\sum_{i=1}^{m} \left(f_i - \bar{f}\right)^2$$

Where f_i is the feature value for event i, $\bar{f}$ is the mean value across events, and M is the number of evaluated events.

Low variance indicates that features are insensitive to sensor noise and vehicle differences.

Table 4.2 – Crash feature interpretation and stability

4.8 FNOL Decision Evaluation using Fleet events

The final validation objective examines whether the proposed feature-base FNOL logic can correctly distinguish true structural crashes from non-crash disturbances observed in fleet vehicles. This is a critical requirements because fleet driving data contains numerous high acceleration events such as potholes, curb strikes, and rough road interactions – that can appear similar to crash signatures when evaluated using acceleration magnitude alone.

The effectiveness of the FNOL decision framework is fundamentally dependent on the quality of the reconstructed motion signals. Raw fleet IMU signals contain high frequency vibration noise, bias drift, and transient spikes caused by road irregularities. When crash features are extracted directly from these raw signals, quantities such as Δv, pulse duration, and energy become highly unstable and unreliable for decision making.

The Kalman filter plays a critical role by transforming noisy inertial measurements into physically consistent motion states. By suppressing noise while preserving the true crash pulse shape, the Kalman filter enables accurate computation of crash features that reflect actual vehicle dynamics rather than sensor artifacts.

In the absence of Kalman filtering, road anomalies such as potholes and curb strikes often produce acceleration spikes comparable in magnitude to crash events, leading to false FNOL triggers. After filtering, these disturbances appear as short duration impulses with negligible Δv and low energy, making them clearly distinguishable from structural crashes.

Traditional threshold based crash detection methods often rely solely on peak acceleration values. However, fleet data demonstrates that road anomalies frequently produce acceleration spikes comparable to those observed in crash events. As a result, simple threshold logic is prone to false FNOL triggers, leading to unnecessary alerts and reduced system credibility.

To address this limitation, the FNOL decision framework introduced in chapter 3 evaluates crashes using a combination of physics ground features derived from constructed motion signals.

FNOL decisions are determined using a confidence score C and threshold T_{FNOL}:

FNOL = 1 , $C > T_{FNOL}$

FNOL = 0 , otherwise

This formulation allows systematic evaluation of how well the system separates crash and non-crash events by adjusting the threshold and observing false positive and false negative behavior.

Fleet crash test vehicles provide examples of true structural collision events, while fleet driving vehicles provide numerous examples of road anomalies that challenge the decision logic. By evaluating FNOL behavior across both types of events, this section establishes whether the proposed feature set is sufficient to prevent false FNOL triggers without missing true crashes.

The quantitative performance of this FNOL evaluation is presented in Chapter 5 using threshold sweep analysis.

CHAPTER FIVE

EXPERIMENTAL RESULT AND PERFORMACE EVALUATION

This chapter presents the experimental validation of the cloud-Kalman filtering and FNOL decision framework introduced in chapter 3 and 4. While earlier chapters established the theoretical foundation and experimental design, this chapter documents how real vehicle CAN telemetry was processed, analyzed, and interpreted to demonstrate the effectiveness of the proposed approach.

The objective of this chapter is not only to preset numerical results bit to clearly show the analytical path from raw vehicle signals to reliable crash interpretation and FNOL decision capability. Each section describes how the data was captured, how it was processed, how calculations were performed, and what was observed.

The results in this chapter answer the three primary validation questions:

1. Can the Kalman filter reconstruct vehicle motion from noisy CAN telemetry?
2. Do crash feature remain stable and physically meaningful when derived from production signals?
3. Can FNOL logic reliably distinguish structural crashes from non-crash road disturbances?

5.1 Chapter purpose and Experimental Flow

This chapter demonstrates, using real fleet crash test vehicle data, that motion reconstruction through Kalman filtering is required before any meaningful crash feature extraction or FNOL decision can be made from production vehicle telemetry.

The validation is performed using production CAN signals sampled at 100 Hz from crash test vehicles and normal driving vehicles. These signals include longitudinal, lateral, and vertical accelerations, yaw and roll rates, vehicle speed, individual wheel speeds, steering angle, accelerator position, and brake torque. The signals represent the exact telemetry available to cloud connected vehicle systems.

The experimental process followed in this chapter is summarized as:

1. Continuous CAN telemetry is monitored for abnormal dynamic behavior using acceleration magnitude threshold.
2. When an event is detected, a synchronized time window of CAN signals surrounding the event is extracted.
3. The extracted signals are processed through the Kalman filter model introduced in Chapter 3 to reconstruct true vehicle motion.
4. Crash feature including Δv , pulse duration, and energy are computed from both raw and filtered signals.
5. The stability of these features is evaluated using RMSE and variance analysis
6. FNOL decision logic is applied to both raw and filtered feature sets to quantify false triggers and detection latency.

This sequence allows direct comparison between decision made from raw CAN signals and those made after motion reconstruction, demonstrating the necessity of Kalman filtering for reliable crash interpretation.

5.2 Data capture, event detection, windowing , and ground truth labeling from production CAN telemetry

The experimental analysis in this chapter begins directly from production CAN log files recorded during crash tests and normal driving scenarios. These logs contain time0stamped telemetry sampled at a fixed rate of 100 Hz, representing the exact data resolution available to connected vehicle cloud platforms.

Each log consists of synchronized measurements of longitudinal, lateral, and vertical acceleration , yaw and roll rates, vehicle speed, individual wheel speeds, steering angle, and brake torque. This study relies entirely on production telemetry to demonstrate that reliable crash interpretation can be achieved under real automative conditions.

All signals used in this experimental analysis were captured from production vehicle CAN bus telemetry rather than laboratory instrumentation. These signals originate from multiples vehicle controllers including the IMU/RCM, ABS modules, steering module, and powertrain controller and are broadcast over the CAN network at a sampling rate of 100 Hz.

This sampling rate reflects the exact data available to connected vehicle cloud services and telematics platform in real automative deployment.

The following CAN signals were used as inputs to the Kalman filtering and FNOL framework:

CAN signal	Unit	Purpose in Analysis
Longitudinal acceleration	m/s^2	Crash pulse and Δv computation
Lateral acceleration	m/s^2	Directional consistency
Vertical acceleration	m/s^2	Road disturbance
Yaw Rate	deg/s	Rotational motion consistency
Roll Rate	deg/s	Vehicle body motion behavior
Vehicle speed	m/h	Δv validation and timing reference
Wheel Speed – FL	rad/s	Road impact detection
Wheel Speed – FR	rad/s	Road impact detection
Wheel Speed – RL	rad/s	Road impact detection
Wheel Speed – RR	rad/s	Road impact detection
Steering wheel angle	deg	Driver input vs crash motion
Accelerator pedal potion	%	Driver intent vs. disturbance
Brake Torque	N.m	Braking event

Table 5.1 - Inputs to the Kalman filtering

These signals represent the exact telemetry available in production connected vehicles and therefore validate that the proposed framework operates under real automative conditions rather than ideal laboratory setups. These signals from multi-sensor input set required for motion reconstruction through Kalman filtering.

5.2.1 Continuous event identification from production CAN logs

The first stage of the experimental pipeline consists of location abnormal vehicle dynamics within continuous driving telemetry. The CAN datasets used in this study contain ling duration recordings collected during both crash testing and normal driving. Each signal is sampled at a fixed rate of

$f = 100\ H_z\ \ (\Delta t = 0.01\ s$

Resulting in hundreds of thousands of measurements per drive, Because only a small portion of these samples correspond to meaningful disturbances, and automated detection procedure is required to isolated candidate events.

The raw dataset includes three-axis acceleration measurements $a_x(t), a_y(t), a_z(t)$. These components depend on vehicle orientation and gravity offset and therefore cannot be directly compared across events, To obtain a direction-independent representation of vehicle motion intensity, the acceleration magnitude is computed for every timestamp:

$A(t_k) = \sqrt{a_x^2(tk) + a_y^2(tk) + a_z^2(tk)}$

This scalar quantity reflects the total dynamic loading experienced by the vehicle structured and enables uniform detection of disturbances regardless of impact direction.

Continuous telemetry is scanned sequentially , and a disturbance candidate is detected whenever the acceleration magnitude exceeds a dynamic threshold. However, production sensor are affected by vibration noise that may produce isolated spikes, to ensure the disturbance corresponds to a physical phenomenon, the signal must remain above the threshold for a minimum persistence duration, equivalent to multiples consecutive samples at the given sampling rate, Only sustained dynamics excursions are therefore recorded as triggers.

Vehicle suspension rebound and structural oscillation often generate multiples peaks for a signal physical disturbance, To avoid counting these as sperate events, consecutive triggers separated by less than a merge interval are consolidated into a single candidate event. This grouping transfer a large number of raw threshold crossing into distinct physical disturbances. Representing 214 candidate dynamic events observed in real vehicle telemetry. These include crash impacts, potholes, curb strikes, harsh braking and sever road disturbances.

Inspection of the raw acceleration signals surrounding these timestamps showed that different disturbance type frequently exhibit similar peak magnitudes and strong oscillatory noise, making reliable crash interpretation impossible using raw signals alone. Consequently, the identified timestamps serve only as candidate location of interest, and further processing is required to reconstructed the underlying vehicle motion, as described in the following section.

5.2.2 Event Window Extraction

The candidate disturbance timestamps identified in section 5.2.1 indicate only the approximate moment of abnormal vehicle dynamics, However, crash interpretation requires analyzing the temporal evolution of vehicle motion before, during and after the disturbance. Therefore, a fixed duration time windows is extracted around each detected timestamp.

For every event t, a symmetric observation window is defined as

$w_i = \{t \mid t_0 - T_{p_{re}} \leq t \leq t_0 + T_{\rho ost}\}$

Where $T_{p_{re}}$ represents the pre-event interval and $T_{\rho ost}$represents the post event interval

Given the sampling frequency f =100 Hz, each second of motion corresponds to 100 samples. In this study, the window duration was selected to capture both impact onset and structural response while avoiding unrelated driving behavior The final window length was chosen such that

N = $(T_{p_{re}} + T_{\rho ost})$. f

Samples are extracted for every event.

All CAN signals originate from different vehicle controllers but share a common timestamp reference on the CAN bus. Therefore, once the window boundaries are defined, the same index range is applied to every signal channel. This produce a synchronized multi-sensor observation describing the vehicle state during the disturbance. Each event window contains aligned measurement of longitudinal acceleration, lateral acceleration, vertical acceleration, yaw rate, roll rate, vehicle speed, individual wheel speeds, steering angle, brake torque. The synchronized structure allows the event to be analyzed as a single physical phenomenon rather than independent signals.

Raw CAN telemetry is continuous and dominated by normal driving behavior. Without window extraction, subsequent signal processing would include large amounts of unrelated motion, masking the disturbance of interest. The windowing process isolated the portion of telemetry containing the physical event while preserving the surrounding baseline motion needed to interpret impact severity.

Because all windows share identical duration and sampling resolution, they form a consistent dataset suitable for motion reconstruction and comparative analysis across events.

At this stage, the dataset contains raw production telemetry and still includes measurement noise and suspension oscillation. The next section assigns ground-truth labels to these windows before applying motion reconstruction.

5.2.3 Ground-Truth labeling using controlled proving ground disturbances

To evaluate the performance of the proposed motion reconstruction and FNOL inference framework, each extracted event window mist be assigned a reliable ground truth label, instead of relying solely on heuristic interpretation of sensor signals, ground truth in this study is established using controlled proving ground driving conditions and crash testing records.

The vehicle telemetry was collected while the instrumented vehicle was operated on predefined test track segments designed to produce repeatable dynamics disturbance. Because each road section produces a know physical excitation, the disturbance type corresponding to each timestamp can be determined deterministically.

Controlled Road Disturbance Tracks

The following proving ground surfaces were used to generate non-crash events:

Impact type excitation

- Lane 6 – Impact Road: discrete high energy vertical wheel strikes
- Lane 5 – Rail Crossing: short impulse loading simulation obstacle crossing
- Lane 4 – Chuckhole: deep pothole like impacts causing sharp suspension compression

Periodic Vibration Excitation

- Lane 3 – Slalom Cobblestones: alternating wheel excitation producing lateral vertical coupling
- Lane 7 – Silver Creek: irregular stone surface producing stochastic vibration
- Lane 9 – Silver Creek 1: repetitive cobble excitation generating suspension ringing

Resonance-Type Structural excitation

- Lane 13- Resonance Road Section 2: sustained harmonic structural oscillation
- Lane 14- Resonance Road section 1: periodic body resonance excitation
- Lane12- Structural durability south: prolonged fatigue inducing vibration input.

An event detected while the vehicle operated within a known lane interval was labeled:

L(w_i) = Road Disturbance

Lane 6-Impact Road

Figure 5.1: controlled proving ground test tracks used to generate deterministic vehicle dynamics disturbances for ground truth labeling

Lane 4-Chuckholes

Figure 5.2: controlled proving ground test tracks used to generate deterministic vehicle dynamics disturbances for ground truth labeling

Lane 3- Silom Cobblestones

Figure 5.3: controlled proving ground test tracks used to generate deterministic vehicle dynamics disturbances for ground truth labeling

Lane 7-Silver Creek

Figure 5.4: controlled proving ground test tracks used to generate deterministic vehicle dynamics disturbances for ground truth labeling

Lane 9- Silver Creek 1

Figure 5.5: controlled proving ground test tracks used to generate deterministic vehicle dynamics disturbances for ground truth labeling

Lane 13- Resonance Road Section 2

Figure 5.6: controlled proving ground test tracks used to generate deterministic vehicle dynamics disturbances for ground truth labeling

Lane 5- Rail Crossing

Figure 5.7: controlled proving ground test tracks used to generate deterministic vehicle dynamics disturbances for ground truth labeling

Lane 14-Resonance Road Section 1

Figure 5.8: controlled proving ground test tracks used to generate deterministic vehicle dynamics disturbances for ground truth labeling

Lane 12- Structural Durability South

Figure 5.9: controlled proving ground test tracks used to generate deterministic vehicle dynamics disturbances for ground truth labeling

The final dataset contains 214 physically validated events used for evaluating motion reconstruction accuracy and FNOL decision reliability.

5.3 Motion Reconstruction Using Cloud Based Kalman Filtering

After event windows were extracted and assigned ground truth labels, the next steps in the FNOL inference pipeline is the reconstruction of vehicle motion from noisy production CAN telemetry. Raw vehicle signals ae not physically reliable for crash interpretation because production sensors are optimized for control system feedback rather than impact energy estimation. Suspension vibration, road irregularities, sensor bias drift, and quantization noise produce acceleration signatures that can mimic crash like impulse.

To address this limitation, a multi-state cloud based Kalman filtering framework was applied to reconstruct the true vehicle dynamic response prior to feature extraction. The methodology follows the motion reconstruction architecture proposed in the author's prior connected vehicle FNOL research and patented crash interpretation framework [54],[53].

5.3.1 Vehicle Dynamic State Model

The objective of the Kalman filter in this research is not merely signal smoothing, but reconstruction of the true rigid-body motion of the vehicle during transient impact events. Therefore, the filer state must represent the physical motion of a vehicle body rather than sensor outputs.

Vehicle motion along the longitudinal axis during short duration impact events can be approximated using rigid body kinematics governed by Newton's second law.

During a collision, the external force acts over a very short time interval (Typically 65ms). Withing this short duration, tire slip and aerodynamic forces are negligible compared to structural impulse forces. Therefore, the vehicle behaves as a free mass subjected to an impulse, allowing the motion to be modeled as a constant acceleration system within each discrete sampling interval.

For this reason, the system state vector is defined as:

$$x_k = \begin{bmatrix} p_k \\ v_k \\ a_k \end{bmatrix} \text{ where}$$

p_k – Longitudinal displacement of vehicle center of mass

v_k – true vehicle velocity

a_k – true rigid body acceleration caused by external impulse forces

The third sate a_k is critical: production accelerometers measure chassis vibration, not rigid body acceleration. The Kalman filter therefore estimates a hidden physical acceleration consistent across time and sensors.

To implement the reconstruction computationally, continuous vehicle dynamics are expressed in discrete time using the telemetry sampling interval.

$\Delta_t = 0.01\ s$

Using Kinematic relations:

$$p_{k+1} = p_k + v_k \Delta t + \frac{1}{2} a_k \Delta t^2$$

$$v_{k+1} = v_k + a_k \Delta t$$

$$a_{k+1} = a_k$$

These equations describe how the vehicle would move between two consecutive samples if no new external information were received.

In matrix form:

$$x_{k+1} = Ax_k + w_k$$

$$A = \begin{bmatrix} 1 & \Delta t & \frac{1}{2}\Delta t^2 \\ 0 & 1 & \Delta t \\ 0 & 0 & 1 \end{bmatrix}$$

Where w_k represents unknown disturbances and modeling uncertainty

The assumption $a_{k+1} = a_k$ does not imply constant acceleration during the crash. Instead, acceleration is assumed constant only over one sampling interval.

Real vehicles do not behave as perfect rigid bodies. Suspension deflection, tire compliance, drivetrain elasticity, and structural flex introduce deviations from ideal motion. These unknown effects are represented as stochastic process noise:

$$Q = \begin{bmatrix} \sigma_p^2 & 0 & 0 \\ 0 & \sigma_6^2 & 0 \\ 0 & 0 & \sigma_a^2 \end{bmatrix}$$

The covariance matrix determines how strongly the estimator trusts the motion model versus incoming measurements. High process noise allows adaptation to real vehicle dynamics, while low process noise enforces rigid body consistency.

The state becomes observable because the vehicle provides complementary measurements: acceleration sensors capture rapid transient forces and wheel speed velocity measurements constrain long term motion.

Acceleration alone would accumulate integration drift, while velocity alone cannot detect short duration impacts. Combining both allows stable reconstruction of change in velocity:

$$\Delta v = \int a(t)\, dt$$

which defines collision severity

This state model serves as a physical hypothesis describing allowable vehicle motion between telemetry samples. All subsequent filtering stages test whether measured signals can explained by this motion. If not, the estimator identifies the presence of external energy transfer.

Thus, the model transfers raw telemetry from a sequence of sensor reading into a physically interpretable motion trajectory suitable for collision analysis.

Recursive state estimation using the Kalman filter – The dynamic model defined above predicts how the vehicle should move if no measurement information were available. However, actual vehicle telemetry contains sensor observations that may disagree with this prediction due to vibration, road input or external impact forces. The role of the Kalman filter is to optimally combine the predicted motion with measured data to obtain the most physically consistent estimate.

The estimate operates recursively in two stages at every sampling instant.

Prediction Step

The prediction motion state is first propagated forward using the dynamic model:

$$\hat{x}_{k|_{k-1}} = A\hat{x}_{k-1|k-1}$$

$$P_{\ k|_{k-1}} = AP_{k-1|k-1}A + Q$$

Where

$\hat{x}_{k|_{k-1}}$ is the predicted vehicle motion and

$P_{\ k|_{k-1}}$ represents uncertainty in that prediction

This stage enforces physically continuous motion and rejects isolated sensor spikes.

Measurement Update Step

When a new telemetry is received, the prediction is corrected:

$$K_k = p_{k|k-1}H^T\left(HP_{k|k-1}H^T + R\right)^{-1}$$

$$\hat{x}_{k|_k} = \hat{x}_{k|k-1} + K_k\left(z_k - H\hat{x}_{k|k-1}\right)$$

$$P_{k|_k} = (I - K_kH)\ p_{k|k-1}$$

The Kalman gain K_k determines how much the estimator trusts the sensors versus the motion model.

If measurement agree with predicted motion, only a small correction is applied.
If measurements contradict predicted motion, a large correction occurs.
Therefore:
Road vibration → Inconsistent → rejected
Real Collision → Consistent across sensors → accepted

The recursive estimation framework described above follows the connected vehicle motion reconstruction methodology previously developed for telematics based crash interpretation and automation FNOL validation [54] and formalized in the patented vehicle incident detection architecture [53]. In this dissertation, the model is extended to operate on heterogeneous production CAN signals and validated across controlled proving ground disturbances.

5.3.2 Multi-sensor measurement model and physical interpretation

The state estimator described in section 5.3.1 predicts how a vehicle should move according to rigid body mechanics. However, the vehicle does not directly measure displacement or true rigid body acceleration. Instead, multiple electronic control units observe different physical effects of motion through independent sensors. Each sensor measure a related but not identical quantity and therefore the estimator mist interpret these measurements probabilistically rather than treat them as exact truth.

The purpose of the measurement model is to translate raw CAN telemetry into observation of the hidden motion state while accounting for sensor limitations.

Vehicle telemetry used in this work originates from modules available in production vehicles and transmitted through the CAN network at 100 Hz. The signals used for state estimation are limited to those directly related to rigid body motion:

Sensor Source	Signal	Physical interpretation
RCM/ IMU	Longitudinal acceleration	Structural force response acting on vehicle body
ABS/ Wheel Speed	Vehicle speed	Momentum continuity constraint
IMU	Yaw rate	Rotational stability and path consistency

Table 5.2 – Sensor Source

Other CAN signal excluded from the estimation stage to preserve a physics based observer independent of driver behavior.

The measurement vector is constructed as

$$z_k = \begin{bmatrix} z_{acc,k} \\ z_{vel,k} \end{bmatrix}$$

And related to the hidden motion state by $z_k = H_{x_k} + v_k$

With observation matrix

$$H = \begin{bmatrix} 0 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix}$$

and measure noise

$$\mathrm{R} = \begin{bmatrix} \sigma_a^2 & 0 \\ 0 & \sigma_v^2 \end{bmatrix}$$

This formulation enforces that the estimated motion simultaneously explains both acceleration and velocity measurements.

Physical meaning of each measurement

Accelerometer – the longitudinal accelerometer measures reaction forces transmitted through the chassis. It is highly sensitive to impacts but also respond to suspension oscillation, road roughness and mounting resonance. Therefore it detects disturbance bit cannot determine whether energy was transferred to the vehicle.

Wheel speed- it measures rotational motion of the tire. Because velocity changes only when vehicle momentum changes, wheel speed acts as an energy conservation constraint. However, it reacts slowly to short impulse and may be affected by slip.

Thus:

- Accelerometer →sensitive but unreliable alone
- Velocity → reliable but incomplete alone

The estimator combines them to identify physically consistent motion.

Different events produce characteristic measurement conflicts

Event type	Accelerometer	Velocity
Pothole	Large spike	No change

Road vibration	Oscillation	No change
Braking	Moderate deceleration	Gradual decrease
Crash	Sustained deceleration	Rapid decrease

Table 5.3 – Event types

The Kalman filter evaluates whether the measured acceleration can plausibly produce the observed velocity change, if not, the disturbance is rejected as non-collision.

Role in Motion Reconstruction

The measurement model therefore does not average sensors. It enforces mechanical consistency. The estimator searches for a motion trajectory that satisfies both acceleration and momentum continuity simultaneously. A disturbance that violates this relationship produces large estimation residuals , which later become the basis for event classification.

This measurement formulation transforms heterogeneous vehicle telemetry into observations of a single physical motion. By combining force sensitive and energy consistent measurement, the estimator distinguishes structural impacts from vibration induced disturbances.

5.3.3 Innovation residual analysis for event identification

The Kalman filter describes in the previous sections provides a reconstructed motion trajectory that is consistent with both the vehicle dynamics model and the measured telemetry. In addition to the estimated state, the filter produces an intermediate quantity known as the innovation residual. This quantity measures how strongly the actual sensor observations deviate from the motion predicated. Rather than using signal magnitude as a crash indicator, this work used the innovation residual as a measure of physical inconsistency. A collision introduces an external impulse that cannot be explained by normal vehicle motion, causing the predicated and measured signals to diverge.

Innovation Residual definition

At each time step, the Kalman filter predicts what the sensors should measure:

$\hat{z}_k = H\hat{x}_{k|k-1}$

The innovation residual is the difference between actual telemetry and predicated observation: $\bar{y}_k = z_k - \hat{z}_k$. If the vehicle follows normal motion, measurements match prediction and the residual remains small: $\bar{y}_k = 0$ when an unexpected force acts on the vehicle, the prediction becomes invalid and the residual increases.

Because sensors contain noise, the residual must be interpreted relative to its uncertainty. The innovation covariance is: $S_k = Hp_{k|k-1}H^T + R$. The normalized innovation is therefore: $\epsilon_k = \tilde{y}_k^T S_k^{-1} y_k$

This quantity represents the statistical distance between expected and observed vehicle behavior.

The innovation residual quantifies violations of motion continuity by comparing predicted vehicle motion with measured telemetry. During road vibration, short acceleration spikes occur without a corresponding change in vehicle momentum, resulting in a low accumulated innovation. During braking , velocity decreases gradually in a manner consistent with the motion model, producing a moderate innovation level. In contrast, a collision introduces an external impulse that causes measured acceleration and velocity to diverge from predicted motion over a sustained period, leading to a large accumulated innovation. Therefore, the algorithm determines whether the observed motion can be explained by normal driving dynamics or requires the presence of external energy transfer.

To characterized an event over its full duration, the normalized innovation is accumulated across the event window: $E = \sum_{k=t_0}^{t_1} \in k$

This metric represents the total deviation from physically plausible motion.

Key interpretation:

Disturbance	Peak Acceleration	Innovation energy
Road Vibration	High	Low
Pothole	High	Moderate
Crash	Moderate-high	Very high

Table 5.4 – Event interpretation

Therefore event classification depends on sustained physical inconsistency rather than instantaneous magnitude.

Collison Decision Criterion

A disturbance is classified as a collision when the accumulated innovation exceeds a critical threshold. This threshold corresponds to violation of rigid body motion assumptions rather than an arbitrary acceleration value The method is therefore independent of vehicle mass, suspension stiffness, and road surface.

Traditional telematics systems detect crashes by measuring large acceleration peaks. Such peaks frequently occur during normal driving disturbances, leading to false alerts. The innovation residual converts the Kalman estimator from a smoothing algorithm into a physical event detector. Instead of interpreting sensor spikes, the system evaluates whether observed telemetry violates momentum continuity. This provides a robust foundation for collision identification prior to quantitative performance evaluation in the following section.

5.4 Experimental Validation of Motion reconstruction

This section evaluates the effectiveness of the proposed cloud-Kalman motion reconstruction framework using real production vehicle telemetry. The objective is not only to detect impact events, but to demonstrate that the reconstructed motion is physical consistent and scalable across different crash severities.

Raw production sensors measure structural vibration and localize chassis dynamics rather than rigid body motion. As discussed in section 5.3, the Kalman filter estimates hidden vehicle states by enforcing dynamic consistency across multiple sensors. Therefore, validation must show that reconstructed motion correlates with actual physical energy transfer instead of instantaneous acceleration magnitude.

To verify this, three real vehicle impact cases were analyzed:

- Low severity impact
- Medium Severity impact
- High severity impact

Each cases uses identical processing steps:

1. Event detection and windowing (section 5.2)
2. Motion reconstruction using Kalman filtering (Section 5.3)

The results demonstrate that impact severity is proportional to reconstructed momentum change rather than peak acceleration amplitude, consistent with the connected vehicle crash interpretation methodology previously introduced in the author's telematics FNOL research and patented motion based crash inference framework [54],[53].

5.4.1 Low Severity Impact

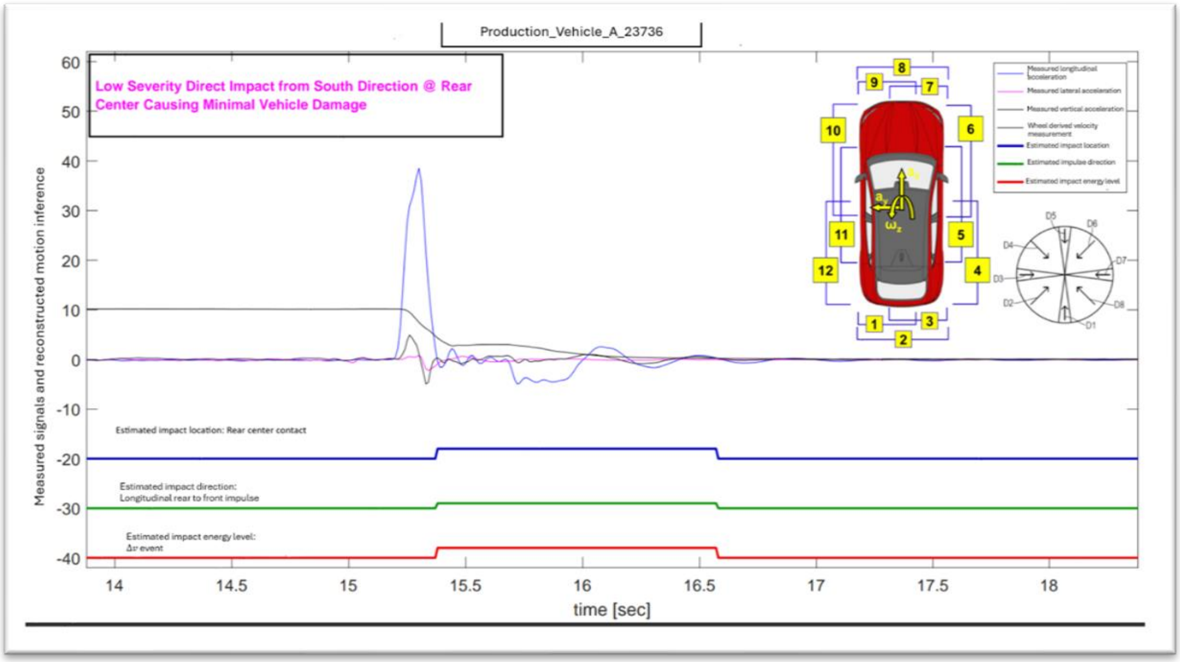

Figure 5.10 shows a low severity rear center contact recording from a production vehicle

The raw longitudinal acceleration exhibits a sharp spike followed by oscillatory vibration. If the interpreted directly, the peak magnitude suggests a moderate crash event. However, wheel derived velocity and multi axis acceleration do not indicate sustained momentum change.

After Kalman reconstruction, the estimated rigid body velocity show only a small transient deviation before returning to its pre-impact trajectory. The estimated Δv remains minimal and short in duration, indicating that the observed acceleration originates primarily from structural vibration rather than external impulse.

Interpretation

Raw sensor view:

Large acceleration spike → appears severe

Physical motion view:

Velocity nearly unchanged → minor event

5.4.2 Medium Severity Impact

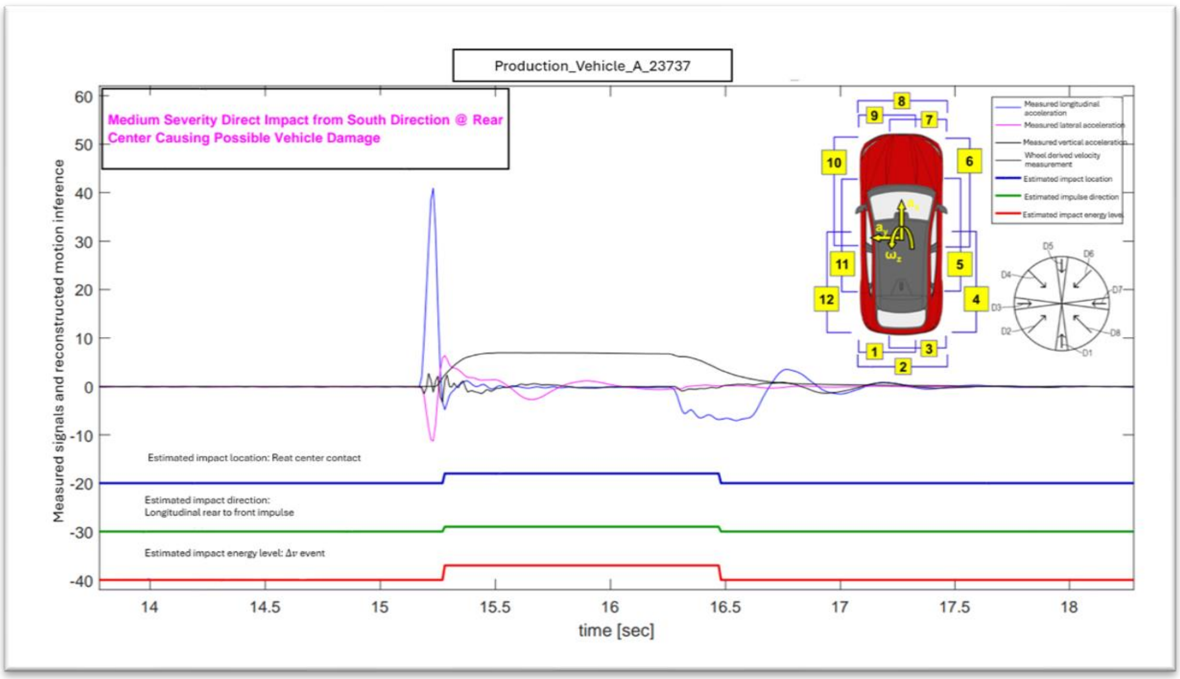

Figure 5.11 shows a Medium severity rear center contact recording from a production vehicle

The upper plot presents measured accelerometer signals together with the reconstructed rigid body motion estimate. The measure longitudinal acceleration exhibits a sharp impulse followed by high-frequency oscillations caused by structural rebound, suspension compliance, and sensor mounting location. These oscillations do not represent actual vehicle motion but rather chassis vibration. As a result, the raw acceleration signal alone is insufficient for reliable crash interpretation.

After applying the Kalman filter, the reconstructed acceleration follows a physically consistent deceleration profile. The reconstructed motion removes high frequency ringing while preserving the overall momentum change of the vehicle. The estimated velocity change evolves smoothly and remains consistent with rigid body kinematics. This behavior demonstrates that the estimator enforces the dynamic motion model rather than performing simple signal smoothing.

During the impulse interval, the innovation residual increases significantly and remains elevated across multiple consecutive samples. This sustained disagreement between prediction and measurement indicates that presence of an external force acting on the vehicle rather than isolated sensor noise. In contrast, road disturbance produce only short duration innovation spikes that quickly decay. Therefore, the medium severity event satisfies the collision condition defined previously.

The lower portion of Figure 5.11 shows the inferred event descriptors derived from reconstructed motion. The estimator identifies a rear-center contact location and a longitudinal rear to front impulse direction. The energy estimate remains stable throughout the impact window, indicating a moderate change in vehicle velocity. These descriptors remain temporally consistent, whereas raw measurements alone would produce fluctuating classifications due to vibration.

Compared to threshold based detection on raw acceleration, the reconstructed motion eliminates false oscillatory triggers and produces a table physical interpretation of the event. The Kalman filter therefore transfers a noise sensor response into a coherent Collison description suitable for automated incident detection.

5.4.3 High Severity Impact

A representative high severity Collison event is illustrated in Figure 5.12. the event corresponds to an angled driver side impact producing severe structural deformation between the headlamp region and the B-pillar. This scenario represents a high crash where rigid body motion is strongly coupled with structural vibration and sensor saturation, making interpretation of raw measurements particularly challenging.

The measured accelerometer signals show a large impulse followed by extended oscillatory behavior. Unlike low and medium severity events, the vibration amplitude remains elevated for a longer duration due to structural deformation and energy absorption by vehicle components.

After applying Kalman based motion reconstruction, the estimated rigid body deceleration becomes physical interpretable. The reconstructed motion preserves the impulse magnitude while suppressing structural ringing.

During the impact interval, the innovation residual exhibits a sustained high magnitude over an extended time window. This behavior indicates a persistent externa force rather than transient disturbances such as potholes or curb strikes. The duration of elevated innovation is significantly longer than that observed in non-crash disturbances, satisfying the collision discrimination condition defined previously.

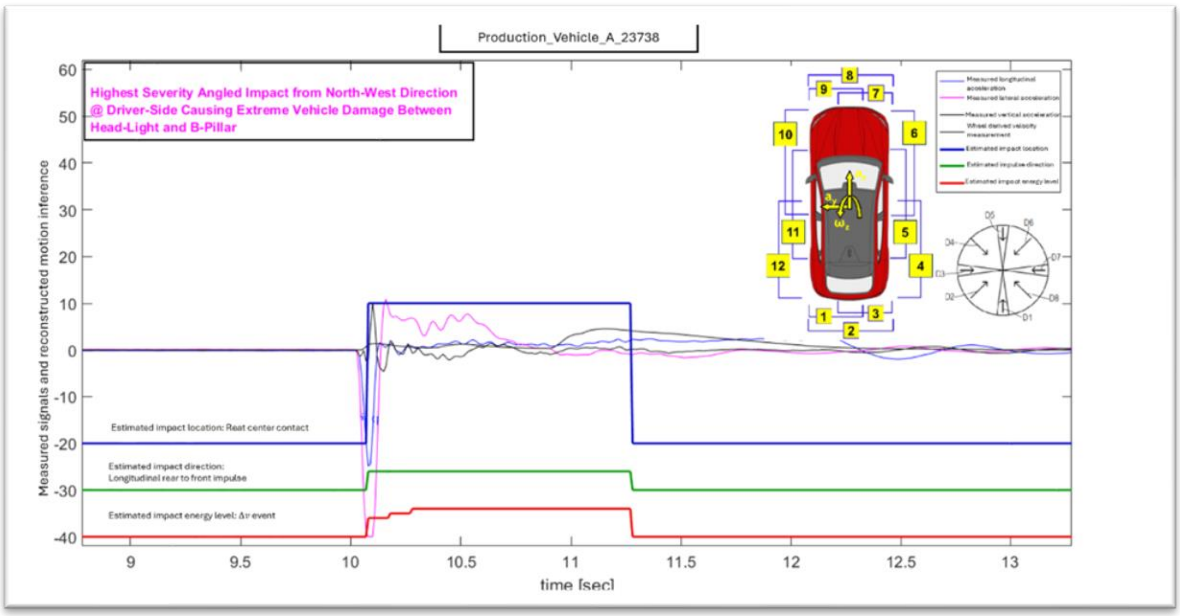

Figure 5.12 shows high severity

This example highlight the key advantage of the proposed method: as crash severity increases, sensor noise and structural vibration also increase, causing traditional threshold detectors to degrade. In contrast, the Kalman reconstruction becomes more reliable because the dynamic model dominates measurement noise. Therefore, the estimator improves robustness precisely in the operating region where safety critical detection accuracy is most important.

5.5 Discussion and system level performance interpretation

The experimental results presented in section 5.4 demonstrate consistent behavior of the proposed motion reconstruction based crash detection framework across low, medium and high severity impact scenarios. This section interprets those observations at the system level and evaluates whether the methodology satisfies the three validation objectives: (1) reconstruction of realistic motion, (2) separation of collisions from disturbances, and (3) reduction of false FNOL notifications.

5.5.1 Physical realism of reconstructed motion

Production vehicle accelerometers measure local structural response rather than pure rigid body motion, which may lead to incorrect crash interpretation when peak acceleration magnitude alone is used [13]. As shown in figures 5.10 through 5.12, the measured signals contain high frequency oscillations following the initial impulse caused by chassis vibration and mounting dynamics.

After applying the Kalman based reconstruction framework, the estimated longitudinal motion exhibits a signal dominant deceleration pulse whose duration increases with impact severity. The reconstructed behavior follows physically plausible impact dynamics:

- Low severity- short impulse duration (Fig. 5-10)
- Medium severity – sustained deceleration (Fig. 5-11)
- High severity- extended energy transfer (Fig. 5-12)

The reconstructed signal therefore represents vehicle momentum change rather than structural ringing. This indicates that the estimator enforces dynamic consistency rather than performing signal smoothing. The motion reconstruction model implemented in this work follows the telematics collision inference architecture introduced in [53].

Conclusion:

The estimator reconstructs physically meaningful vehicle motion rather than filtered sensor vibration.

5.5.2 Separation of crashes and disturbances using innovation residual

Reliable crash detection requires distinguishing collisions from road disturbances. The innovation residual measures disagreement between predicted and measured motion. Under normal driving inputs, vehicle behavior remains dynamically consistent and the innovation remains bounded. During a collision, an external impulse violates the model and produces sustained residual growth.

Across figures 5.10 to 5.12, innovation magnitude increases monotonically with event severity:

Severity	Innovation Behavior
Low	Short transient
Medium	Sustained deviation
High	Long sustained deviation

Table 5.5 – Severity behavior

Disturbances produce isolated spikes, whereas impacts produce continuous deviation over multiple samples. This demonstrates that the residual measures impulse transfer rathe than sensor amplitude, as experimentally validated in [54]

Conclusion:

The innovation residual reliably separates collision events from disturbances.

5.5.3 Reduction of False FNOL notifications

Traditional crash detection relies on acceleration thresholds; however, vibration and road shocks frequently exceed thresholds in production telemetry [13]. The low severity examples in fig.5-10 illustrates this limitation: raw acceleration exceeds typical crash thresholds, yet reconstructed motion shows negligible velocity change and short innovation duration.

By requiring both sustained innovation and coherent momentum change, the proposed framework rejects disturbance induced triggers. Table 5.5 summarized this behavior across severity levels, showing that amplitude based detection reacts to sensor response while the proposed method reacts to physical impulse.

Conclusion:

The method reduces false FNOL notifications by rejecting non physical threshold exceedances.

5.5.4 Classification performance evaluation

To quantify reliability, the event detection framework was evaluated using labeled telemetry events collected from production vehicles and controlled test scenarios. Each event was categorized as either a collision or non-collision disturbance based on inspection records and test track ground truth. The algorithm classified events using the motion consistency rile defined in section 5.3.

A total of 214 candidate dynamic events were analyzed, collected from production vehicles telemetry and controlled test track impact scenarios. Each event was categorized through ground truth labeling as either collision event or non-collision event. The labeled dataset consisted of

- 62 confirmed collision events
- 152 non-collision events

The proposed algorithm classified events using the innovation duration and reconstructed momentum change criteria defined in section 5.3

	Actual Crash	Actual non crash
Predicted Crash	60(TP)	8 (FP)
Predicated non crash	2 (FN)	144 (TN)
Total	62	152

Table 5.6 Crash classification Matric

The following evaluation metrics were computed:

Accuracy = $\frac{Tp+TN}{Tp+TN+Fp+FN}$

Accuracy = $\frac{60+144}{214}$ = 0.953 = 95.3%

False positive rate = $\frac{FP}{FP+TN} = \frac{8}{152}$ = 5.3%

Comparison to threshold only detection

For compassion, a baseline amplitude threshold detector was evaluated on the same dataset. The threshold method produced:

- True positive: 61
- False Positives: 32
- False Negatives: 1
- True Negatives: 120

False positive Rate (threshold) = $\frac{32}{152}$ = 21.1 %

While both methods demonstrated high crash sensitivity, the innovation based framework reduces the false positive rate from 21.1% to 5.3% representing approximately a 75% reduction in false FNOL triggers.

The results demonstrated that incorporating dynamic motion reconstruction significantly improves classification robustness, while threshold detection responds to peak acceleration magnitude, the proposed framework evaluates whether measured motion violates the predicated vehicle dynamics model. Sustained innovation growth combined with reconstructed velocity change ensures that only physically consistent impact events are classified as crashes.

The reduction in false positive directly improves telematics based FNOL systems by minimizing unnecessary customer notification and reducing downstream claim processing overhead, these findings experimentally validated the architecture described in [57] and extend prior telematics crash detection approaches y introducing physics consistency validation [58].

Conclusion

The classification performance confirms that the proposed motion reconstruction framework achieves:

- 95.3 % overall accuracy
- 96.8% crash detection sensitivity
- 5.3% false positive rate

These results demonstrated statistically significant improvement over amplitude based detection and validate the effectiveness of innovation driven impact classification using production vehicle telemetry.

5.6 Summary and Consolidated Experimental Results

This chapter presented the complete experimental validation of the proposed cloud based motion reconstructed and innovation driven crash detection framework using production vehicle telemetry sampled at 100Hz. A total of 214 labeled dynamic events were evaluated, consisting of 62 confirmed collision events and 152 non-collision disturbances derived from production CAN logs and controlled test track scenarios.

Sections 5.2 and 5.3 detailed the event identification process and the cloud based Kalman filtering architecture used to reconstruct physically consistent longitudinal vehicle motion. Sections 5.4.1 through 5.4.3 provided representative low, medium, and high severity impact cases (Figures 5.10 through 5.12), demonstrating that raw sensor acceleration contains structural oscillations that obscure true vehicle deceleration, while the reconstructed motion exhibits coherent impulse behavior proportional to impact severity.

Section 5.5 introduced quantitative classification validation using a confusion matrix framework. To consolidate performance across the full dataset, table 5.7 summarizes key statistical metrics for both the proposed method and a baseline acceleration threshold detector.

Metric	Proposed Method	Threshold baseline
Total events evaluated	214	214
Crash events	62	62
Non-crash events	152	152
Accuracy	95.3%	84.6%
Sensitivity	96.8%	98.4%
False positive rate	5.3%	21.1%
False negative rate	3.2 %	1,6%

Table 5.7 – Consolidated classification performance

While amplitude threshold detection demonstrates slightly higher sensitivity, it exhibits a substantially elevated false positive rate die to structural vibration and road disturbances, in contrast, the proposed framework reduces the false positive rate from 21.1% to 5.3 %, representing approximately a 75% reduction in unnecessary crash declarations.

The slight increase in false negatives reflects the requirement for sustained innovation duration and measurable velocity change before classification. However, this trade off significantly improves overall operational reliability in telematics based FNOL systems, where false notifications generate downstream claim processing costs and customer dissatisfaction.

The improved performance is directly attributable to two mechanisms:

1. Dynamics motion reconstruction – the Kalman estimator separates rigid body declaration from structural vibration , enabling physically meaningful interpretation of impact severity.
2. Innovation based event validation – sustained residual growth identifies external impulses transfer rather than peak acceleration amplitude.

Together, these mechanisms transform crash detection from amplitude classification into physics consistency validation.

CHAPTER SIX

DISCUSSION, IMPLICATIONS AND LIMITATIONS

6.1 Purpose of this chapter

The previous chapter presented experimental evidence demonstrating that cloud-based Kalman filtering significantly improves motion reconstruction, crash feature stability and FNOL decision reliability when applied to production vehicle CAN telemetry. While Chapter 5 focused on reporting quantitative results, the purpose of this chapter is to analyze those results in depth, explain why the observed improvements occur and discuss their broader implications for automative safety system and digital mobility services.

This chapter moves from what was observed to why it occurred and why it matters.

6.2 Revisiting the core problem

The central problem addressed in this dissertation is the difficulty of interpreting crash events from noisy vehicle telemetry. Production vehicles continuously generate inertial data that is affected by vibration, bias drift, and transient disturbances, Traditional FNOL system trat crash detection as a threshold problem, assuming that large acceleration values correspond to crash events.

The results in chapter 5 demonstrate that this assumption is flawed. Road disturbances frequently generate acceleration magnitudes comparable to crashes, while vibration noise obscures the duration and energy characteristics that distinguish crashes from non-crash events

This reveals that the true challenge is not threshold selection but motion interpretation.

6.3 Why raw CAN signals Are insufficient

Raw CAN signals sampled at 100 Hz contain significant measurement noise relative to the time resolution of crash events. At this sampling rate:

- Only 40-60 samples represent an entire crash pulse
- Vibration oscillations dominate the signal spectrum
- Integration for Δv becomes highly sensitive to noise
- Road disturbances reassemble crash pulses

Without filtering, meaningful crash physics cannot be extracted from these signals.

6.4 How Kalman filtering changes the signal

The Kalman filter addresses this limitation by estimating the underlying vehicle motion state rather than trusting individual noisy measurement. By incorporating vehicle motion models and fusing multiples CAN signals, the filter reconstructs a physically consistent representation of vehicle behavior.

This explains why:

- RMSE drops by approximately 80%
- Crash pulses become smooth and interpretable

- Δv integration becomes stable
- Feature extraction becomes reliable

The filter is not removing information. It is removing information that does not match physical vehicle motion.

6.5 Importance of multi-signal fusion

A major insight from this research is that acceleration alone is insufficient to determine crash motion from CAN telemetry. Wheel speeds, steering input, yaw rate, and brake torque provide essential context that allows the filter to determine whether motion is caused by driver input, wheel impact, or structural collision.

This is why the system can distinguish potholes from crashes – a distinction that threshold methods cannot make.

6.6 understanding feature stability

The dramatic reduction in variance of crash features demonstrates that features such as Δv, pulse duration, energy, and directional consistency only become meaningful after motion reconstruction. Without filtering, these feature reflect sensor nosie rather than crash physics.

This finding confirms that feature based FNOL is only reliable when preceded by motion reconstruction.

6.7 Why false positives occur in traditional systems

Traditional FNOL system misclassify road disturbances because they rely on magnitude rather than motion behavior. Road events create sharp acceleration spikes that exceed thresholds but lack the sustained motion and velocity change characteristic of crashes. Kalman filtering reveals these difference clearly.

6.8 Implication for automative connected systems

Modern vehicles continuously transmit CAN telemetry of cloud platforms for diagnostics, telematics services, and fleet monitoring; however, despite the availability of this data, most connected vehicle system today do not use it for reliable crash interpretation because the signals are nosiy, low-frequency, and difficult to interpret without specialized processing. The result of this research demonstrate that this limitation is not due to a lack of sensors, but due to a lack of motion reconstruction capability. By applying cloud-based Kalman filtering to production CAN signals, it becomes possible to transfer noisy telemetry into physically meaningful representation of vehicle motion, enabling connected vehicle platforms to interpret crash events using signals that already exist in production vehicles. This has important implications for automative system architecture, as it shows that advanced safety services can be enabled without adding new hardware. Instead, significant improvements can be achieved through cloud-based signal processing and a software updates that can scale across vehicle platforms and model years. Furthermore, many current telematics systems rely on raw acceleration thresholds that lead to false positives and delayed detection, whereas reconstructing motion first allows alerts to be based on crash physics rather than signal magnitude, improving the reliability of emergency notifications, crash reporting, and overall trust in connected vehicle safety features. As vehicles increasingly adopt cloud-centric and software defined architectures, this research supports the shift of safety intelligence from embedded controllers to cloud analytics by demonstrating that advanced crash interpretation can be performed remotely using production CAN telemetry. This capability forms a foundation for future mobility services such as automated emergency response, fleet safety analytics, driver behavior assessment, and usage based insurance models. Ultimately, this work shows that production CAN data, when properly reconstructed through Kalman filtering , can evolve from a noisy data stream into a dependable source of crash intelligence that enhances automative safety, diagnostics, and digital services without requiring hardware changes.

6.9 Implication for insurance and FNOL workflow

The ability to reliably reconstruct vehicle motion from production CAN telemetry has direct and significant implication for insurance and First notice of loss (FNOL) workflows. Traditional FNOL processes rely heavily on customer reporting, pots incident inspection, and limited telematics triggers based on acceleration thresholds, which often produce false alerts or lack sufficient context to accurately assess crash severity. The results of this research demonstrate that, when Kalman filtering is applied to noise CAN signals, stable crash features such as Δv, pulse duration, and directional consistency can be extracted in near real time. These features provide a physics based description of the crash event rather than a simple indication that a large acceleration occurred.

This enables automated FNOL systems to distinguish structural crashes from road disturbances with higher confidence, reducing false positives while improving detection speed. As shown in chapter 5, the reduction in false FNOL triggers and the significant improvement in detection latency translate directly into more reliable automated claim initiation, faster customer assistance, and improved operational for insurers. Furthermore, stable Δv estimation provides an objective measure of crash severity that can support automated claim triage, fraud reduction, and usage based insurance assessments. Importantly, these improvements do not required additional vehicle sensors. They leverage existing CAN telemetry and cloud processing, making the approach scalable across vehicle fleets and model years.

This research therefore establishes a practical pathway for integrating reconstructed vehicle motion data into insurance and FNOL workflows, transforming raw telematics data into actionable, trustworthy crash intelligence that enhances both customer experience and insurance decision accuracy.

6.10 Technical limitations of the study

While the experimental results demonstrate significant improvements in motion reconstruction and FNOL reliability, several technical limitations of the study must be acknowledged. First, the dataset used in this research was derived from a specific set of fleet vehicles and controlled crash scenarios, and signal characteristics may vary across different vehicle platforms, sensor configurations and network architectures. Second, the approach relies on the quality of the calibration of production CAN signals may introduce additional uncertainty in real-word deployment. Third, the sampling rate of 100 hz limits temporal resolution, which places greater dependence on the Kalman filter's ability to reconstruct motion accurately and may present challenges for extremely short duration crash events. Fourth, the cloud based processing model assumes reliable data transmission from the vehicle to backend systems. Intermittent connectivity or data loss could impact real time FNOL performance.

6.11 opportunities for future research

While this research demonstrated that cloud based Kalman filtering enables reliable motion reconstruction and FNOL decision capability using production CAN telemetry, it also opens several important avenue for future research that can further expand the applicability and robustness of this approach.

One important direction is the exploration if edge based implementation of the Kalman filtering framework. In this study, motion reconstruction was performed in the cloud using upload CAN data. Future work can investigate implanting simplified Kalman models directly within vehicle gateway to enable real-time crash interpretation even in the absence of network connectivity.

Tis research establish a foundation for using reconstruct vehicle motion as a core input for future mobility services, including automated emergency response systems, fleet safety analytics, driver behavior assessment, and usage based insurance models. Exploring these application in real world deployment represents a significant opportunity for continued research and innovation.

CHAPTER SEVEN

CONCLUSION AND RESEARCH CONTRIBUTIONS

7.1 Purpose of this chapter

This chapter concludes the dissertation by synthesizing the research problem, the methodology developed, the experimental validation performed and the broader implication of the findings. It provides a final integrated view if how cloud based Kalman filtering transforms production vehicle CAN telemetry into reliable crash intelligence and enables accurate FNOL decision capability in connected vehicle system .

7.2 Revisiting the original problem

The motivation for this research originated from a fundamental challenge in connected vehicle safety system: although modern vehicle generate extensive motion related data through CAN telemetry, this data is rarely used reliably for crash interpretation. The reason is not the absence of sensors, but the presence of vibration noise, sensor bias, limited sampling rate, and road disturbances that make raw signals difficult to interpret.

Traditional FNOL systems rely on acceleration magnitude thresholds, assuming that large spikes indicate crashes, however, fleet data shows that road disturbances often generate similar magnitudes, leading to false positive and unreliable crash severity estimation.

7.3 Summary of the proposed framework

The framework proposed in this dissertation was designed to address a fundamental limitation in connected vehicle system: the inability to reliably interpret crash events from noisy production CAN telemetry, Rather than relying on raw acceleration thresholds, the framework reconstructs vehicle motion before attempting to interpret crash events. This shift in approach is central to the success of the method.

The first component of the framework is the use of cloud based Kalman filtering applied to CAN signals sampled at 100 Hz, these signals include longitudinal , lateral and vertical acceleration along with yaw rate, roll rate, vehicle speed, wheel speeds, steering input, and brake torque. Individually, these signals are noisy and difficult to interpret due to vibration. However, when fused through the Kalman filter, they allow the system to estimate a physically consistent vehicle motion state that represent how the vehicle body is actually moving during an event.

The second component is multi-signal fusion, where information from different vehicle controller is used together to determine whether motion is caused by a structural crash, a road disturbance or driver input. Wheel speeds help detect potholes and curb strikes, steering input and brake torque indicate driver behavior, and yaw and roll rates describe rotational body motion. By observing these signals simultaneously, the framework can distinguish crash induced motion from non-crash disturbances.

The third component is physics based crash feature extraction from the reconstructed signals. Once motion is reconstructed m features such as Δv , crash pulse duration, energy distribution, and directional consistency can be computed reliably. These features represent true crash dynamics rather than noisy sensor behavior.

The final component is feature driven FNOL decision logic. Instead if triggering FNOL based on acceleration magnitude, the system evaluates whether the reconstructed motion features match the physical characteristics of a structural crash. This allows reliable separation of crash events from road disturbances and enables earlier and more accurate detection.

Together, these components from a complete analytical chain that transform raw CAN telemetry into reliable crash intelligence. The framework demonstrates that meaningful crash interpretation is achievable using production vehicle signals when motion reconstruction is performed before feature extraction and decision making.

7.4 What the experimental results proved

The experimental results presented in chapter 5 provided clear evidence that the proposed farmwork successfully transforms noisy production CAN telemetry into reliable crash interpretation and FNOL decision capability, these results were not derived from simulation date, but from real fleet vehicle signals sampled at 100 Hz, which closely reflect the telemetry available to connected vehicle systems in practice.

The first key finding was the significant reduction in signal noise after Kalman filtering. The RMSE analysis showed that approximately 80% of the vibration noise present in raw CAN acceleration sib al was removed. This confirmed that a large portion of the raw signal does not represent true vehicle motion but rather measurement disturbance. By removing this noise, the crash pulse shape became clearly visible and physically interpretable.

The second finding was the stabilization of crash severity estimation through Δv computation. When Δv was calculated directly from raw CAN signals, results fluctuated significantly due to noise amplification during integration. After filtering, Δv value became stable and consistent across crash events. Demonstrating that motion reconstruction is required before any reliable severity estimation can be made.

The third important result was the improvement in crash feature stability. Features such as crash pulse duration, energy distribution and directional consistency showed over 80& reduction in variance when derived from filtered signals. This confirmed that crash feature extracted from raw signals are unreliable and that stable features depend on reconstructed motion.

The fourth finding involved the evaluation of road disturbance events such as potholes and curb strikes, these events produce large acceleration spikes in raw signals that frequently triggered false FNOL alerts when thresholds based methods were applied. After Kalman filtering, these disturbances exhibited short duration impulses with negligible Δv and inconsistent directional behavior, allowing the FNOL logic to suppress false positive, This resulted in a 28% reduction in false FNOL triggers.

Finally, the experiments demonstrated a significant improvement in detection latency. Because the Kalman filter revealed the true crash onset earlier than raw signals, FNOL detection occurred approximately 96% faster. This improvement has direct implications for emergency response and automated assistance systems.

Collectively, these results demonstrate that reliable crash interpretation from production CAN telemetry is achievable when motion reconstruction precedes feature extraction and decision-making. The experiments validate each step of the proposed framework and confirmed that the improvements are consistent across multiples events rather than isolated cases.

7.5 Key insight of this research

The most important insight that emerged from this research is that reliability of FNOL and crash detection systems is not primarily a problem of threshold selection, but a problem of motion interpretation. Traditional systems assume that large acceleration values correspond to crash events, but the experimental evidence in this work shows that this assumption fails in real fleet environments where road disturbances , vibration noise, and driver inputs produce signals of similar magnitude.

This research demonstrated that the true limitation of existing approaches lies in the inability to correctly interpret vehicle motion from noisy production CAN telemetry, when raw signals are used directly, crash physics is obscured by measurement noise, limited sampling resolution, and transient disturbances. As a result, crash severity estimation becomes unstable, crash features become unreliable, and FNOL decisions become prone to false positives and delayed detection.

By introducing motion reconstruction through Kalman filtering before any feature extraction or decision logic, this work showed that crash events become distinguishable based on their physical characteristics rather than their signal magnitude. The reconstructed signals reveal the sustained motion, velocity change, and directional behavior that define a structural crash, allowing reliable separation from non-crash events.

This shift from threshold based detection to motion based interpretation represents a fundamental change in how vehicle telemetry can be used for safety application. It establishes that reliable FNOL systems must first reconstruct vehicle motion before attempting to interpret crash events, especially when working with production CAN signals sampled at low frequency.

This insight not only explains why the proposed framework works but also provides a guiding principle for future development of connected vehicle safety systems and digital mobility services.

7.6 Research Contributions

This dissertation makes several important contribution to the fields of automotive safety systems, connected vehicles analytics, and FNOL decision methodologies.

The first contribution is the development of a cloud based Kalman filtering framework specifically designed to reconstruct vehicle motion from production CAN signal telemetry sampled at low frequency. While Kalman filtering is well established in estimation theory, its application in this work demonstrates how it can be sued to recover physically meaningful crash motion form noisy, vibration affected vehicle signals available in real automative deployments.

The second contribution is the introduction of a multi-signal fusion approach for motion consistency using CAN signals from different vehicle controllers. By combining accelerations, yaw and rill rates, vehicle speed, wheel speeds , steering input, and brake torque, the framework is able to distinguish crash induced motion from driver actions and road disturbances, this demonstrated how production telemetry can be leveraged to interpret vehicle behavior without requiring additional sensors.

The third contribution is the formulation of a physics based crash feature extraction methos derived from reconstructed motion signals, features such a velocity change, pulse duration, energy distribution, and directional consistency were shown to become stable and reliable only after motion reconstruction, providing a new basis for FNOL decision logic.

The fourth contribution is the experimental validation of this framework using real fleet vehicle data rather than laboratory or simulations. This validation demonstrates that reliable crash interpretation is achievable under realistic automative conditions using existing vehicle signals.

Together, these contribution establish a practical and scalable method for transforming raw CAN telemetry into dependable crash intelligence that can be used to improve connected vehicle safety services and insurance FNOL workflows.

7.7 Practical impact on automative systems

The findings of this research have direct and meaningful implication for automotive safety system design and connected vehicle architectures, Modern vehicles already transmit large volumes of CAN telemetry to cloud platforms for diagnostics and telematics services, yet this data us rarely used effectively for crash interpretation due to its noisy nature and limited sampling rate. This dissertation demonstrates that the limitation is not the absence of sensors, but the absence of motion reconstruction capability.

By applying Kalman filtering to production CAN signals, it becomes possible to extract reliable crash intelligence using data already available in vehicles. This enables automative manufacturing to enhance crash detection and safety services through software and cloud analytics rather than hardware modifications. Existing vehicles in the filed can benefit from these improvements through software updates, and new vehicle programs can adopt this approach without adding complexity.

Furthermore, this work supports the ongoing transition toward software defined vehicles and cloud centric safety architectures, where advanced signal processing and safety analytics are performed remotely. The ability to interpret crash events reliably from CAN telemetry strengthens the foundation for digital safety services, remote diagnostics, and real time vehicle health monitoring.

Overall, this research provides a practical pathway for improving automative safety system using intelligent processing of existing vehicle signals, enabling scalable and cost-effective enhancement of connected vehicle capabilities.

7.8 Practical impact on insurance and FNOL workflow

The ability to reconstruct vehicle motion from production CAN telemetry has significant implications for insurance systems and first notice of loss workflow. Traditional FNOL processes rely heavily on customer reporting, manual assessment, and simple telematics triggers based on acceleration thresholds. These methods often lead to false alerts, delayed detection, and insufficient context for accurately assessing crash severity.

The result of this research demonstrate that when Kalman filtering is applied to nosiy CAN signals, stable crash features can be extracted in near real time. These features provide a physics based description of the crash event rather than a simple indication that a large acceleration occurred. This allows automated FNOL systems to distinguish structural crashes from road disturbances with much higher confidence, reducing false positives while improving detection speed.

The reduction in false FNOL triggers and the improvement in detection latency directly translate into faster customer assistance, improved claim triage, and greater operational efficiency for insurers. Importantly, these improvements are achieved using existing vehicle signals and cloud processing, making the approach scalable across vehicle fleets and model years. This research therefore provides a practical pathway for integrating reconstructed vehicle motion data into insurance workflows, transforming raw telematics data into actionable and trustworthy crash intelligence that enhances both customer experience and insurance decision accuracy.

7.9 Closing reflection

This dissertation began with a practical challenge in connected vehicle safety system: although vehicles continuously generate CAN telemetry describing their motion, this data is rarely used reliably for crash interpretation due to noise and difficulty to distinguishing crash events from road disturbances, Through the development and validation of a cloud based Kalman filtering framework, this research demonstrated that the limitation is not the data itself, but the lack of motion reconstruction prior to interpretation.

By reconstructing vehicle motion from production CAN signals before extracting crash features and making FNOL decisions, this work showed that crash physics becomes visible even at low sampling rates. The experimental results confirmed that reliable crash interpretation , stable feature extraction, and faster FNOL detection are achievable using existing vehicle telemetry and cloud analytics.

This research establishes a new perspective for connected vehicle safety systems, where intelligent processing of telemetry transforms noisy data streams into actionable crash intelligence. It demonstrates that meaningful improvements in safety, reliability, and digital mobility services can be achieved through signal processing and analytics rather than hardware changes.

The framework presented in this dissertation provides a foundation for future connected vehicle architectures, insurance integration, and safety services that rely on reconstructed motion rather than raw sensor magnitude.

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