Terrain Identification using Reaction-based Sensor Data in Simulation-driven Terrain-aware Military Logistics

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Abstract. Military planning operations require navigating constantly changing environments. To support decision-makers, innovative concepts are essential for automatically generating effective solutions tailored to specific logistics operations. These tools aim to accelerate planning procedures, minimize risks, and reduce operating costs. This paper introduces a simulation-based optimization framework designed to enhance the mobility of military vehicles through terrain-aware navigation. It specifically examines a key component of the framework: terrain identification. This challenge is addressed using unsupervised methods, ensuring applicability even in unfamiliar operational settings. The experimental findings demonstrate promising results in identifying terrain characteristics, particularly in discerning surface waviness, slant, and curvature.

Introduction

The mobility of supplies, equipment, and personnel is crucial to the success of land-based military missions. Unlike civilian logistics, which often prioritize the shortest and fastest routes, military operations must consider factors such as environmental uncertainty [17], route vulnerability [16], and terrain passability [14] when determining the most suitable logistics routes.

Furthermore, military operations often extend across geographically diverse regions, where terrain conditions have a direct impact on their specific effectiveness [14].

Therefore, planners must carefully assess terrain characteristics such as landform features, soil conditions, and slope degree when preparing military logistics plans.

The terrain encountered by military land vehicles often falls outside typical mapped areas, leaving planners with limited information regarding its topology. In such scenarios, battlefield commanders rely on terrain analysts to interpret the geographic features of an area and assess their impact on the military mission [18].

Over time, this process has evolved from a predominantly manual endeavor to one increasingly reliant on computer-based systems [15]. One aspect of terrain analysis that can be addressed through computational means is terrain identification. This field of research involves estimating ground characteristics (e.g., cohesion, curvature, inclination) or categorizing terrain types (e.g., gravel, asphalt, sand) by collecting diverse sensor data under various road conditions and analyzing vehicle responses to the terrain.

Numerous researchers have made significant contributions to terrain identification methodologies. Among these, supervised learning techniques such as Support Vector Machines [1, 10], Decision Trees [12], Neural Networks [9, 13], and Gaussian Process Regression [11] have emerged as popular choices. Although these approaches have proven effective, they often require prior human intervention or additional hardware, such as laser line striping sensors, for data labeling. Conversely, unsupervised approaches do not require labeled data and can be directly applied in scenarios where the external environment is unknown.

In addition to the configuration of the learning algorithm, the accuracy of a terrain identification strategy depends on the data it receives. Various sensors can be mounted on the vehicle to collect this data.

Cameras [4, 5], lidars [7, 8], and accelerometers [1, 2, 3] stand out as prominent choices in recent research. Each sensor type has its limitations [6]. For instance, vision-based sensors such as cameras and lidars are sensitive to weather conditions that reduce visibility, such as fog or rain, whereas reaction-based sensors such as accelerometers are sensitive to speed and load variations. Despite this disadvantage, reaction-based techniques demonstrate strong cost-effectiveness and robustness across diverse terrain types [19].

This study focuses on solving the terrain identification problem, aiming to differentiate distinct terrain characteristics such as roughness, waviness, slant, and curvature. The approach involves conducting multiple test drives at military test sites to collect reaction-based data, including acceleration, roll, pitch, and angular rate, captured by an accelerometer and a gyroscope. Initially, the signal data undergo windowing, followed by the segmentation of each route into predetermined lengths.

Subsequently, the unsupervised learning algorithm Multivariate K-Means is used to differentiate between terrain characteristics. We employ the Dynamic Time Warping (DTW) algorithm to calculate the pairwise proximity between road segments.

Moreover, this research introduces a simulation-driven logistics framework that integrates terrain identification, scheduling, and vehicle routing processes to assist planners in developing terrain-aware logistics strategies.

The plans generated by this framework are designed to optimize the utilization of available assets by considering surface characteristics when determining efficient transportation routes. Within the broader logistics context, this approach offers the potential to improve operational efficiency and achieve substantial cost savings.

In addition to immediate reductions in fuel and personnel expenses, it can also contribute to lowering long-term vehicle maintenance costs. This is achieved by implementing intelligent routing strategies that minimize vehicle wear and tear, thereby extending vehicle lifespan and reducing the frequency of repairs and replacements.

1 Conceptual Approach of a Simulation-based Terrain-aware Logistics Framework

Developing military logistics strategies presents a significant challenge in optimizing asset scheduling and route selection for the efficient transportation of personnel, equipment, and supplies to designated destinations. This challenge is further increased by the absence of basic infrastructure in certain locations and the diverse terrain conditions encountered during transit. Additionally, different vehicles are tailored for navigating specific types of terrain. Some are designed for rough, steep terrain with obstacles, while others perform better on smooth, paved roads.

To ensure effective and efficient transportation operations, it is essential to consider the mobility capabilities of vehicles across various surfaces, along with critical logistics factors such as route length, transport duration, and delivery time requirements.

To address these challenges, we introduce the simulation-based logistics framework depicted in Figure 1. The primary objective of this framework is to assist planners in developing efficient military transportation systems by focusing on sustainable resource management and enhancing vehicle mobility across favorable terrain conditions.

The framework begins by prioritizing the identification of terrain characteristics along the routes. These details, along with information on road networks, vehicle availability, and load requirements for transportation between origin and destination points, serve as inputs.

Subsequently, the framework proceeds to optimize fleet utilization. The scheduling component determines which loads should be transported by each vehicle and in what sequence, aiming to minimize costs while satisfying constraints such as vehicle capacities.

Following scheduling, the routing process uses the scheduled assets to establish logistics routes. This process extends beyond selecting the shortest and fastest paths by incorporating terrain conditions. As certain terrains disproportionately affect vehicle performance and wear, selected routes must align with the mobility characteristics of the vehicles.

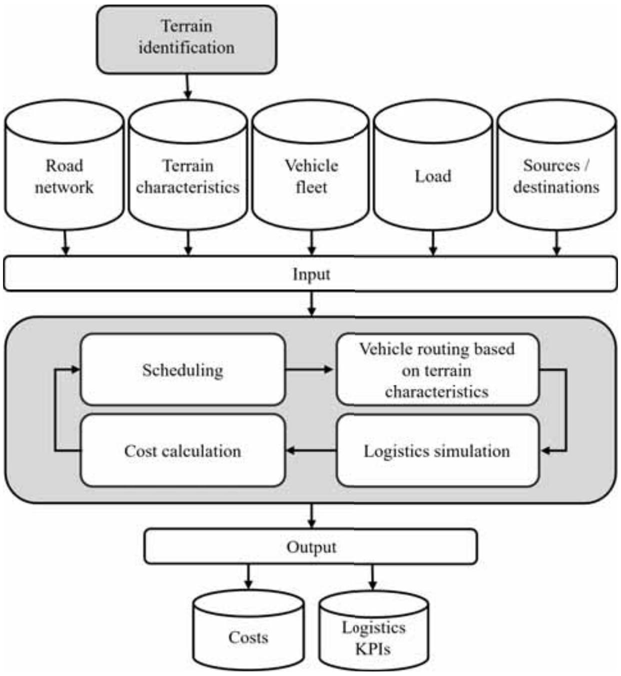


Figure 1: Conceptual model of the proposed simulation-driven terrain-aware logistics framework.

During the simulation phase, logistics plans are executed, and the behavior of simulation agents is monitored. Each transportation task is evaluated using a cost function designed to minimize both duration and cost, while accounting for travel feasibility across different surfaces.

Given the critical role of terrain characteristics in terrain-aware logistics, terrain identification is explored throughout the remainder of this paper.

2 Terrain Identification

This section explores terrain identification, a key component of the logistics framework detailed in Section 1. This process is essential for enabling the computation of terrain-aware logistics routes, as it provides critical information about the interaction between vehicles and the underlying surface conditions.

2.1 Problem Description

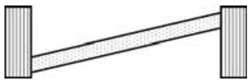
We address the challenge of terrain identification using reaction-based sensor measurements collected from vehicles operating in diverse environments.

The primary objective is to differentiate between specific terrain characteristics such as roughness (Figure 2a), waviness (Figure 2b), slant (Figure 2c), and curvature (Figure 2d), even in scenarios where prior knowledge of the terrain is limited or unavailable.

This is achieved through analyzing unique signal patterns captured by standard sensors like accelerometers and gyroscopes, which record the dynamic interaction between the vehicle and the terrain.
To accomplish this task, we introduce the technique detailed in Section 2.2.

(a) Roughness (lateral cross-section)

(b) Waviness (lateral cross-section)



(c) Slant (frontal cross-section)

(d) Curvature (driver's perspective)

Figure 2: Terrain characteristics under investigation.

2.2 Solution Approach

We propose the methodology illustrated in Figure 3 for terrain identification. This approach relies on data acquired from reaction-based sensors during vehicle operation on various road surfaces.

In the preprocessing phase, the input data are subjected to windowing and segmentation to generate frames for feature extraction. Subsequently, the unsupervised learning technique Multivariate K-Means is applied to identify distinct terrain characteristics.

In the upcoming paragraphs, each component of the terrain identification approach will be elaborated.

Data Acquisition. Over the course of 24 test runs at a military test site, data were collected from multiple ground surfaces exhibiting varying degrees of roughness, waviness, slant, and curvature.

For this purpose, a military vehicle traveled approximately 500 km, equipped with an accelerometer, a tri-axial gyroscope, and a Global Positioning System (GPS). Each sensor recorded data at a sampling rate of 500 Hz.

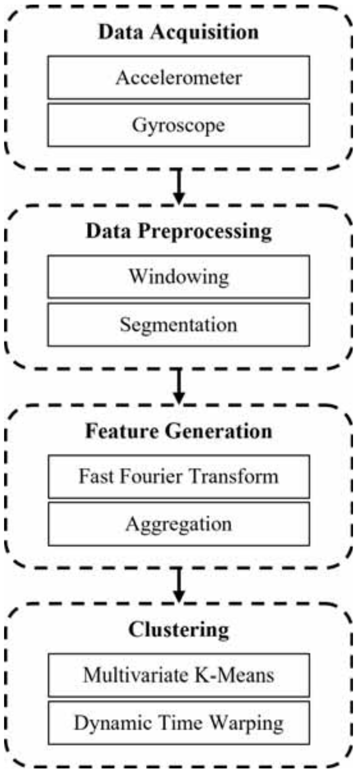


Figure 3: Proposed terrain identification methodology.

To mitigate the speed dependency of reaction-based terrain identification, the vehicle was driven at varying speeds ranging from 5 to 45 km/h.

Data Preprocessing. The preprocessing phase involves two key steps: windowing and segmentation.

Windowing is a technique used to transform sequential data, such as the dataset under consideration, into a format suitable for traditional machine learning algorithms [22].

Additionally, it helps reduce computational complexity. This process involves dividing the sensor data into non-overlapping frames, each consisting of 500 samples, corresponding to one second of data given a sampling frequency of 500 Hz.

Clustering entire routes poses challenges in detecting local similarities. Conversely, clustering individual observations fails to produce cohesive patterns and instead results in fragmented clusters across multiple terrain categories.

To address this issue, we partition each test drive into segments of 40 m, approximately five times the length of the vehicle. Each segment is treated as an individual observation.

Feature Generation. The sensor data in the time domain, including tri-axial acceleration, tri-axial rotation rate, roll, and pitch, are converted into the frequency domain using the Fast Fourier Transform (FFT) algorithm.

Features are extracted by considering observations from both the original time-domain representation and its frequency-domain transformation within the previously generated windows. Each window is aggregated into a single output value by computing statistical measures such as the mean, standard deviation, minimum, maximum, and interquartile range. In total, this process yields 80 features.

Clustering. We approach the task of terrain identification by examining similar patterns within segments of routes traversed by vehicles. Since each segment contains multiple observations, the problem inherently becomes multivariate. To handle this complexity, we utilize Multivariate K-Means clustering.

While deep learning–based clustering techniques could also be applied, they tend to be complex, challenging to interpret, and computationally expensive. However, the K-Means method also has its limitations, particularly its sensitivity to the choice of the number of clusters k.

To address this issue, we employ the Silhouette Coefficient, introduced in [23], to determine an optimal number of 9 clusters.

In the clustering process, we use the DTW proximity measure, a technique proposed in [20]. This method offers advantages over conventional Euclidean distance by effectively recognizing similarities between sequences, even when they differ in length or exhibit slight temporal shifts.

For enhanced visualization and evaluation of the clustering results, we adopt the Multivariate T-distributed Stochastic Neighbor Embedding (m-TSNE) technique introduced by [21].

This approach enables the projection of high-dimensional multivariate data onto a lower-dimensional space while preserving similarity relationships between data sequences. Consequently, sequences that are similar in high-dimensional space remain close in the lower-dimensional space.

3 Experimental Results

The solution described above was implemented and evaluated in Python 3.11.5 on a standard PC running Windows 11, equipped with an 11th-generation Intel Core i7-11370H CPU at 3.30 GHz and 16 GB of RAM. Training the model on a preprocessed dataset of 200 MB requires approximately 15 minutes.

The computational complexity of training arises from the large number of pairwise similarities that must be computed, specifically $\binom{N}{2}$, where N denotes the number of route segments.

The 24 trips are partitioned into approximately 12,000 segments, each assigned to one of 9 clusters using the Multivariate K-Means algorithm with 80 features. To enhance visualization of the high-dimensional space, the data are reduced to two dimensions using the m-TSNE method, as shown in Figure 4. Each point in the plot corresponds to a route segment, revealing discernible separation patterns among groups.

While certain groups, particularly those at the periphery, exhibit clear separation from others, observations in the central regions lack well-defined boundaries. Nevertheless, the clustering method captures the underlying structure, with only a few instances dispersed across multiple groups in the two-dimensional space.

Figures 5a–5d illustrate the key features essential for cluster formation. Each displayed feature is aggregated through windowing using the mean function, as detailed in Section 2.2, and is derived from frequency-domain transformations. Analyzing these plots enables the characterization of clusters based on the distinct terrain traits outlined in Figure 2. High signal magnitudes indicate the presence of specific terrain characteristics, while lower magnitudes suggest their absence.

The accelerometer supports the measurement of the vehicle's vertical displacement relative to the ground (z-axis acceleration), facilitating the evaluation of terrain roughness. Notably, cluster $C5$ stands out as representing rough terrain, as shown in Figure 5a.

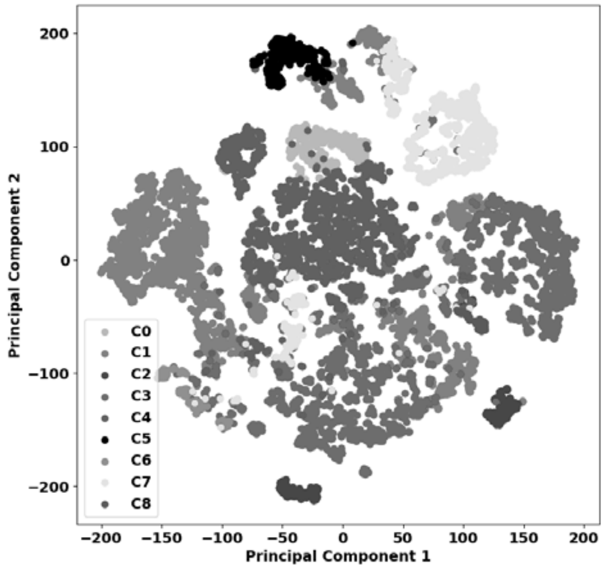
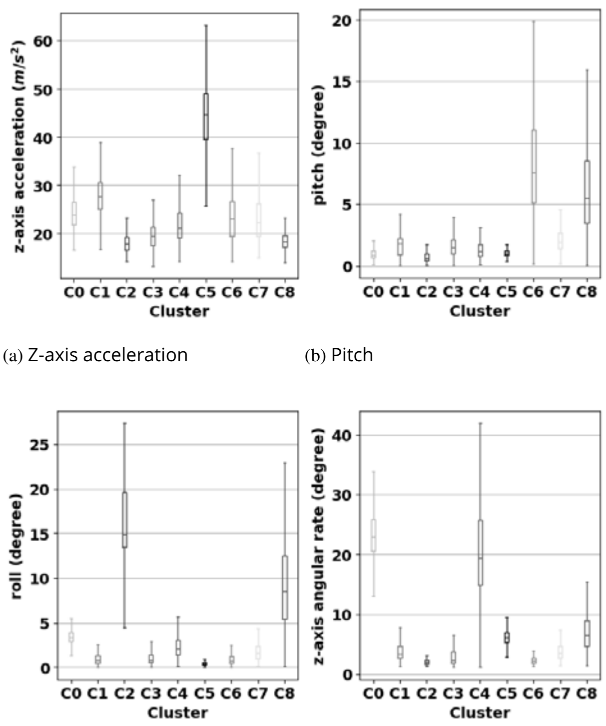


Figure 4: Representation of the two-dimensional m-TSNE components depicting route segments clustered based on the Multivariate K-Means method.

Waviness, in contrast, involves larger, repetitive undulations compared to roughness, resulting in a rocking motion of the vehicle rather than purely vertical acceleration. These movements are captured through pitch measurements from the gyroscope. As depicted in Figure 5b, clusters $C6$ and $C8$ exhibit wavy terrain characteristics. Surface slant, indicative of tilts to the right or left, is discernible via the roll signal. Slanted terrain is observable in clusters $C2$ and $C8$ from Figure 5c. Furthermore, the gyroscope captures the rotational motion of the vehicle, reflecting road curvature, as evident in clusters $C0$ and $C4$ in Figure 5d.

The remaining clusters do not exhibit distinctive terrain characteristics based on the examined features, suggesting that the corresponding road segments are relatively smooth and straight.
An overview of the characteristics exhibited by each cluster is provided in Table 1.

Since the test drives were conducted on a specialized test course, certain segments of the underlying surfaces have known labels. For instance, cluster $C2$ represents the inclined test track, featuring an incline ranging from 20% to 30%. Cluster $C5$ corresponds to the washboard test track, while the sine-wave road is identifiable within cluster $C6$. Cluster $C7$ encompasses cobblestone and gravel surfaces.



(a) Z-axis acceleration (b) Pitch

(c) Roll (d) Z-axis angular rotation

Figure 5: Selection of features employed in the clustering procedure, presented individually for each cluster. These features were derived from raw signals transformed into the frequency domain and aggregated using the mean function during the windowing process.

	Roughness	Waviness	Slant	Curvature
C0	-	-	-	✓
C1	-	-	-	-
C2	-	-	✓	-
C3	-	-	-	-
C4	-	-	-	✓
C5	✓	-	-	-
C6	-	✓	-	-
C7	-	-	-	-
C8	-	✓	✓	-

Table 1: Summary of the terrain characteristics observed within the clusters.

Lastly, cluster $C8$ represents the distortion road, characterized by alternating waves on each side.

Table 2 presents a comparison between the clustering results and the known ground-truth labels.

An examination of the model's performance across clusters reveals that it performs better for certain road types. Specifically, slanted ($C2$) and distorted ($C8$) roads are identified with high precision, recall, and F1-score. However, the model performs less effectively in identifying washboard ($C5$) and sine-wave ($C6$) tracks.

Cluster	Precision	Recall	F1-score
C2	0.99	0.95	0.97
C5	0.92	0.35	0.51
C6	0.86	0.49	0.62
C7	0.93	0.82	0.87
C8	0.93	0.93	0.93

Table 2: Summary of the model performance.

4 Conclusion and Outlook

In military operations, terrain-aware logistics are crucial, particularly when navigating challenging landscapes with limited infrastructure to transport supplies, equipment, and personnel.

In such contexts, logistics planning must consider not only factors such as travel distance, duration, and delivery schedules but also the unique characteristics of the terrain traversed.

In response to this need, this research introduces a simulation-driven terrain-aware framework designed to support decision-makers in improving the mobility of military vehicles by enabling more efficient navigation across favorable terrain conditions. The primary focus of this paper is the terrain identification process, which employs unsupervised methods to distinguish between terrain characteristics even in the absence of prior knowledge of surface conditions.

The experimental findings d emonstrate promising results in discerning roughness, waviness, slant, and curvature from reaction-based signals. Each terrain characteristic is represented by a dominant signal, for instance, high magnitudes of the z-axis acceleration signal indicate rough terrain. Additionally, terrains exhibiting multiple characteristics can be identified by considering multiple signals. For example, higher magnitudes in the pitch and roll signals suggest a wavy and slanted road.

Despite its effectiveness, this approach requires careful consideration in certain areas. As noted in previous research [6], reaction-based terrain identification is sensitive to vehicle speed and load, causing terrain signatures to vary under different operating conditions. For accurate identification, the algorithm must be trained on a diverse dataset encompassing a wide range of speeds and loads.

Moreover, while unsupervised learning is valuable in the absence of prior terrain knowledge, it requires human interpretation of the results. Defining thresholds for specific signals that indicate particular terrain features is essential for precise categorization. Furthermore, the current approach focuses on identifying terrain features but does not quantify their intensity. Future work should incorporate a scoring system to evaluate terrain surfaces based on their characteristics. Identifying specific surface types, such as concrete, grass, or soil, would further enhance the optimization of logistics route planning.

While this paper emphasizes terrain identification, it is essential to implement the subsequent steps of the framework to fully realize its potential in terrain-aware logistics. This includes integrating fleet scheduling, terrain-informed route planning, and simulation-based evaluation to refine and optimize military logistics operations.

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