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 decrease operating costs. This paper introduces a simulation-based optimization framework designed to enhance the mobility of military vehicles through terrain-aware navigation. The paper specifically delves into 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 quickest routes, military operations must consider factors such as environment uncertainty [1], route vulnerability [2], and terrain passability [3] when determining the most suitable logistics routes.

Furthermore, military operations often extend across geographically diverse regions, the condition of the terrain having a direct impact on their effectiveness [3]. 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 little information regarding its topology. In such scenarios, battlefield commanders lean on terrain analysts to interpret geographic features of an area and assess their impact on the military mission [4].

Over time, the process of terrain analysis evolved from a predominantly manual endeavor to one increasingly reliant on computer-based systems [5]. One facet of terrain analysis that can be solved 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 gathering 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 Machine [6, 7], Decision Tree [8], Neural Network [9, 10], or Gaussian Process Regression [11] have emerged as popular choices. Although these approaches have proven effective, they require prior human intervention or additional hardware, such as laser line striping sensors, for data labeling. Conversely, unsupervised approaches do not necessitate 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 the terrain identification strategy depends on the data it receives. Various sensors can be mounted to the vehicle to gather this data. Cameras [12, 13], lidars [14, 15], and accelerometers [6, 16, 17] stand out as prominent choices in recent research. Each sensor type comes with its limitations [18]. For instance, vision-based sensors like cameras and lidars are sensitive to weather conditions that reduce visibility, such as fog or rain, whereas reaction-based sensors like accelerometers are sensitive to speed and load variations. Despite this disadvantage, reaction-based tech-

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niques demonstrate great cost-effectiveness and robustness across diverse terrain types [19].

This study focuses primarily 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 within 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 undergoes windowing, followed by segmenting each route into predetermined lengths. Subsequently, the unsupervised learning algorithm Multivariate K-Means is utilized to differentiate between different terrain characteristics. We employ the Dynamic Time Warping (DTW) algorithm to calculate the pairwise proximity between the road segments.

Moreover, this research introduces a simulation-driven logistics framework that combines terrain identification, scheduling, and vehicle routing processes to assist path planners in conceiving terrain-aware logistics strategies. The plans generated by this framework are designed to optimize the utilization of available asset capacities by considering surface characteristics when determining efficient transportation routes. Within the broader logistics landscape, this approach presents an opportunity to improve operational efficiency and achieve substantial cost savings. In addition to immediate reductions in fuel and personnel expenses, it can also play a role in lowering long-term vehicle maintenance costs. This is achieved by implementing intelligent routing strategies that minimize vehicle wear and tear, ultimately extending their lifespan and decreasing the frequency of repairs and replacements.

The structure of the paper is as follows. Section 1 outlines the logistics framework. The method proposed for terrain identification is detailed in Section 2. Section 3 discusses the findings of the terrain identification process. Finally, Section 4 provides a summary of our conclusions and outlines future work.

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 efficiently transporting personnel, equipment, and supplies to designated destinations. This challenge is heightened by the absence of basic infrastructure at 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, alongside critical logistics factors such as route length, transport duration, and delivery time requirements.

To overcome 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 the mobility of military vehicles in favorable terrain conditions.

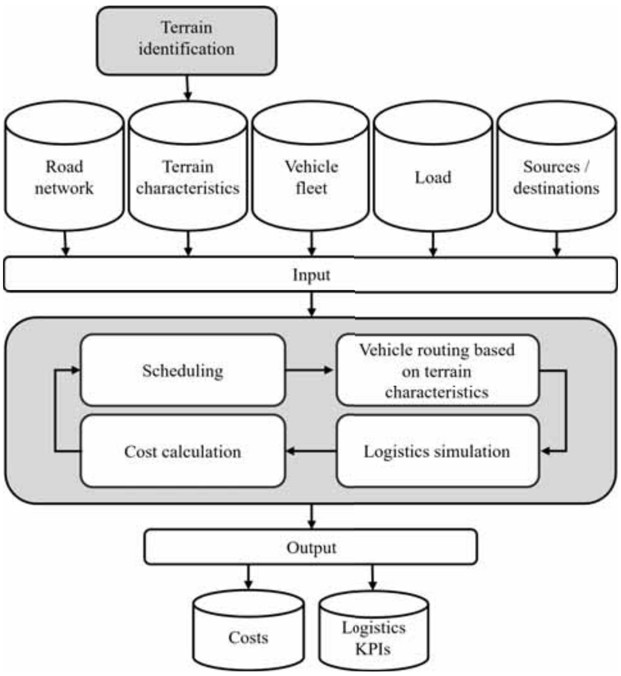


Figure 1: Conceptual model of the proposed simulation-driven terrain-aware logistics framework.

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 vehicle utilization. The scheduling component determines which load should be transported by each vehicle and in what sequence, aiming to minimize costs while meeting constraints such as vehicle capacities.

Following scheduling, the routing process utilizes the scheduled assets to establish logistics routes. This process extends beyond selecting the shortest and fastest paths by considering terrain conditions. As certain terrains disproportionately affect vehicle performance, wear, and tear, selected routes must correspond to the mobility characteristics of the transporter.

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 transportation duration and expenses, taking into account travel feasibility on appropriate surfaces.

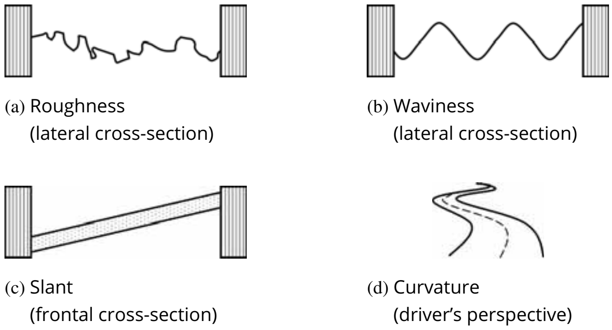
Acknowledging the critical role that terrain characteristics play in terrain-aware logistics, the topic of terrain identification will be explored throughout the remainder of this paper.

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.

2.1 Problem Description

We address the challenge of terrain identification utilizing reaction-based sensor measurements. Our primary objective is to differentiate specific terrain characteristics such as roughness (Figure 2a), waviness (Figure 2b), slant (Figure 2c), and curvature (Figure 2d), even in situations where prior knowledge about the terrain is limited. 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 accomplishing terrain identification. This approach relies on data acquired from reaction-based sensors during vehicle operation on different road surfaces. In the preprocessing phase, the input data is subjected to windowing and segmentation to create frames used for feature generation. Subsequently, the unsupervised learning technique Multivariate K-Means is applied to identify different terrain characteristics.

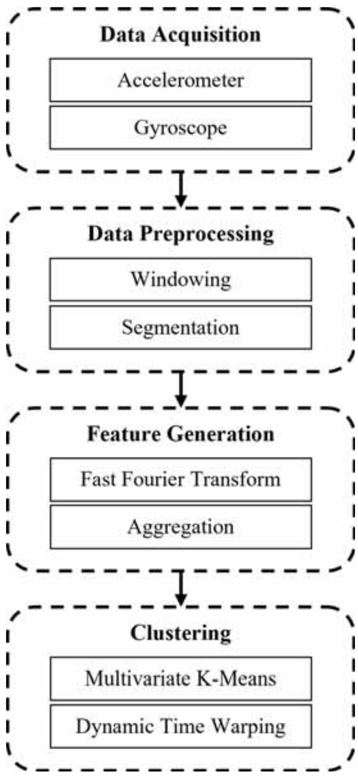


Figure 3: Proposed terrain identification methodology.

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 was gathered from multiple ground surfaces that exhibit different degrees of roughness, waviness, slant, and curvature. For this purpose, a military vehicle covered about 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.

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

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

Windowing is a technique essential for transforming the sequential data, such as the dataset under consideration, into a format that suits traditional machine learning algorithms [20]. Additionally, it helps reduce computational complexity. This process involves dividing the sensor data into non-overlapping frames, with each frame 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 among them. Conversely, clustering each observation separately fails to generate cohesive patterns and instead scatters the clusters across multiple terrain categories. To address this dilemma, we choose to partition each test drive into segments measuring 40 m, approximately five times the length of the vehicle. Each of these partitions is treated as an individual observation.

Feature Generation The sensor data in time domain, including tri-axal acceleration, tri-axal rotation rate, roll, and pitch is 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 previously generated windows. Each window is aggregated to an individual output value by computing statistical measures such as 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 clustering techniques could also be applied, they tend to be complex, challenging to interpret and can generate high computational costs. However, the K-Means method also has its limitations, particularly its sensitivity to the choice of the cluster number k. To address this issue, we employ the Silhouette Coefficient, introduced in [21], to determine an optimal number of 9 clusters.

In the clustering process, we use the DTW proximity measure, a technique proposed in [22]. This method offers advantages over the conventional Euclidean distance by effectively recognizing similarities within sequences, even in cases where they differ in length or experience 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 [23]. This approach enables the projection of multivariate high-dimensional data onto a lower-dimensional space while maintaining the similarity relationships between the data sequences. Consequently, sequences that are similar in high-dimensional space also remain proximate in the lower-dimensional space.

3 EXPERIMENTAL RESULTS

The solution described above has been executed and evaluated in Python 3.11.5 on a typical PC operating on Windows 11, equipped with an 11th generation Intel Core i7-11370H CPU running at 3.30 GHz and 16 GB of RAM. Training the model on a preprocessed dataset of 200MB size requires approximately 15 minutes. The complexity of training arises from the significant number of pairwise similarities that need to be computed, specifically $\binom{N}{2}$, where N represents the count of route segments.

The 24 trips are partitioned into approximately 12 000 segments, each one assigned to one of 9 clusters via the Multivariate K-Means algorithm, utilizing 80 features. To enhance visualization of the high-dimensional space, the data is 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 distinct isolation from others, the observations in the central regions lack clear boundaries. The clustering method captures the underlying pattern, with only a few instances dispersed across multiple groups in the 2D space.

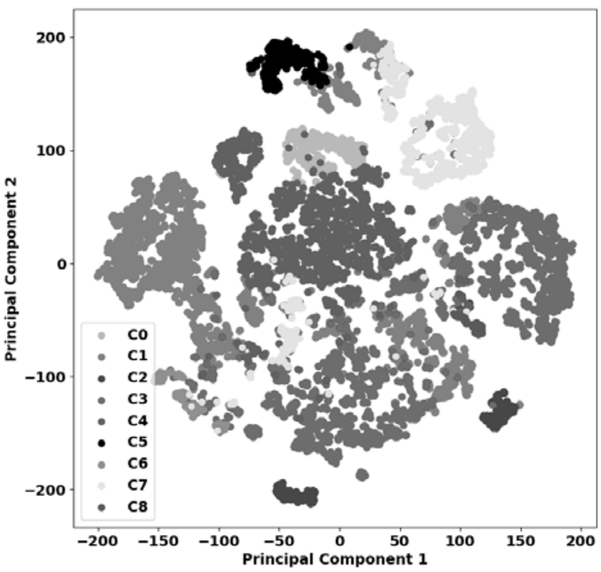
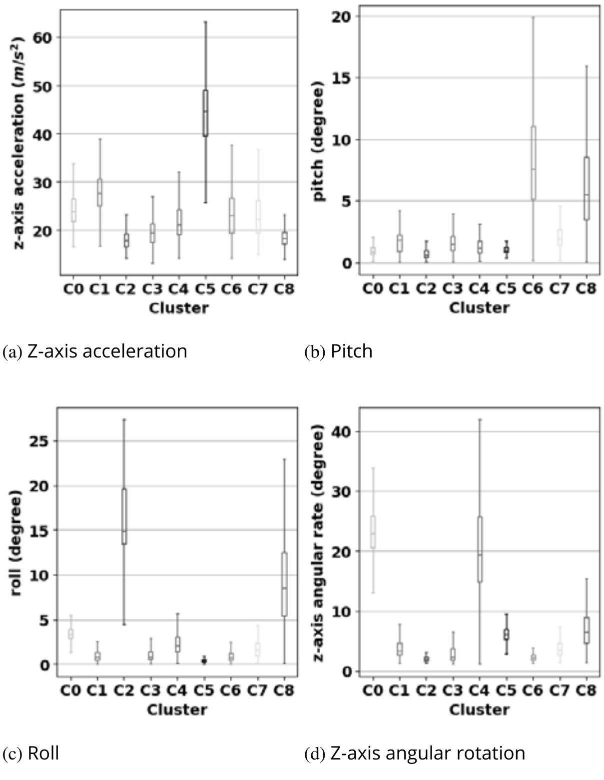


Figure 4: Representation of the two-dimensional m-TSNE components depicting route segments clustered based on the Multivariate K-Means method.

Figures 5a-5d illustrate the key features essential for cluster formation. Each displayed feature undergoes aggregation through windowing using the mean function, as detailed in Section 2.2, 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 emphasize the presence of particular terrain characteristics, while lower magnitudes indicate 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 for exhibiting rough terrain, as evident in Figure 5a. Waviness, on the other hand, involves larger repetitive bumps compared to roughness, resulting in a rocking motion in the vehicle rather than just vertical acceleration. These movements are detected through pitch measurements of the gyroscope. As depicted in Figure 5b, clusters $C6$ and $C8$ highlight 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 can capture the rotational motion of the vehicle, reflecting road curvature, as evident in clusters $C0$ and $C4$ from Figure 5d. The remaining clusters lack distinctive terrain characteristics based on the examined features. This suggests that the road segments within these clusters have likely smooth, straight surfaces. An overview of the characteristics exhibited by each cluster can be found in Table 1.



(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.

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 $C5$ encapsulates the washboard test track, while the sine-wave road is identifiable

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

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

within cluster $C6$. Cluster $C7$ encompasses cobblestone and gravel. Lastly, cluster $C8$ delineates the distortion road, characterized by alternating waves on each side.

Table 2 outlines the comparison between the clustering results and the known true labels. Upon examining the model's performance across the clusters, it becomes evident that the model shows higher performance for certain road types. Specifically, the sloped ($C2$) and the distorted ($C8$) roads are recognized with high precision, recall, and F1-score. However, the model's performance is less satisfactory in identifying the wash-board ($C5$) and the sine-waved ($C6$) 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, especially when navigating through challenging landscapes with sparse infrastructure to transport supplies, equipment, and personnel. In such contexts, logistics planning must encompass not only factors like travel distance, duration, and delivery schedules but also take into consideration the unique characteristics of the terrain traversed.

In response to this necessity, this research introduces a simulation-driven terrain-aware framework designed to support decision-makers in improving the mobility of military vehicles by enabling them to navigate more efficiently through favorable terrain conditions. The primary focus of this paper is the terrain identification process, which utilizes unsupervised methods to distinguish between different terrain characteristics even in the absence of prior knowledge about the surface conditions. The experimental findings demonstrate promising results in discerning roughness, waviness, slant, and curvature through reaction-based signals. Each terrain characteristic is represented by a dominant signal, for instance high magnitudes of the z-axis acceleration signal indicate rough terrains. Additionally, terrains with 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 [18], reaction-based terrain identification is sensitive to the speed and load of the vehicle, causing terrain signatures to vary under different operating conditions. For accurate identification, the algorithm needs to be trained with a diverse dataset that includes a wide range of speeds and loads. Additionally, unsupervised learning, though valuable when no prior knowledge of terrain conditions is available, requires human interpretation of the results. Defining thresholds for specific signals indicating particular road 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 also significantly enhance the optimization of logistics route planning.

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

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