Trajectory-Based Activity Recognition for Earthmoving Operations Using Finite-State Machines

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Abstract

Identifying construction equipment activity states is essential for understanding and optimizing earthmoving operations. Trajectory data can be used to infer semantic equipment activities, while it often leads to inconsistent results when simple rule-based methods are applied. This paper presents a trajectory-based activity recognition approach using finite-state machines (FSMs) for earthmoving operations. The method combines kinematic features from Real-Time Kinematic Global Navigation Satellite Systems (RTK-GNSS) trajectories with spatial constraints and predecessor rules to infer activity states of excavators and dump trucks. A real-world earthmoving case study demonstrates that the proposed FSM-based approach captures cyclic operational patterns. The identified activity states provide a reliable basis for downstream operational analysis and simulation, supporting data-driven construction productivity and emission management.

Keywords

Trajectory tracking; Earthmoving operations; Finite-state machine; Activity recognition; RTK-GNSS; Construction automation

1 Introduction

Earthmoving operations are fundamental to infrastructure and building construction, characterized by repetitive and cyclic interactions among heavy construction equipment, such as excavators and dump trucks. The performance of these operations is strongly influenced by how equipment activities are coordinated over time and space. As a result, accurate identification of equipment activity states is required for analyzing productivity, utilization, and operational inefficiencies in earthmoving processes, and for supporting downstream applications such as simulation-based planning and performance assessment. Effective site management requires continuous monitoring of productivity metrics, such as cycle times and utilization rates, to identify bottlenecks [1,2].

Recent advances in Real-Time Kinematic Global Navigation Satellite Systems (RTK-GNSS) have enabled the continuous collection of high-precision trajectory data from construction equipment [3,4]. Such data provides detailed information to infer equipment movement patterns and interactions on site. However, raw trajectory data do not directly represent semantic activity states of equipment, such as *Load*, *Haul*, *Dump*, *Idle*, or *Wait* for dump trucks. Simple rule-based approaches that rely solely on speed or position thresholds often suffer from noisy state transitions and spatiotemporal inconsistencies, especially in congested and dynamic construction environments [5].

To address these challenges, various activity recognition methods have been explored, including rule-based logic, machine learning models, and vision-based approaches [6,7]. While data-driven methods can achieve high classification accuracy, they typically require large labeled datasets and lack interpretability, which limits their practical deployment on construction sites. In contrast, finite-state machines (FSMs) provide an interpretable and structured way to model cyclic equipment operations by explicitly encoding allowable states and transitions. An FSM is a computational model that represents a system as a set of discrete states and allowable transitions between them. By incorporating predecessor constraints, FSMs improve temporal consistency and robustness in activity recognition for construction equipment [5]. In the context of earthmoving operations, FSMs are well suited to describe repetitive operational cycles, where equipment typically transitions through sequential states such as loading, hauling, dumping, and returning.

This paper presents a trajectory-based activity recognition method for earthmoving operations using FSMs. The proposed approach integrates kinematic features derived from RTK-GNSS trajectories with spatial context and predecessor rules to infer temporally consistent activity states of excavators and dump trucks. The identified activity states directly support operation-level analysis and simulation-based applications, enabling data-driven evaluation of earthmoving performance under real-world site conditions.

2 Related Work

Existing research on construction equipment monitoring has primarily focused on collecting and analyzing sensory data to characterize on-site movement and utilization. While trajectory data offers rich insights into the spatiotemporal patterns of construction equipment, effective operational analysis requires the capability to translate raw motion into meaningful activity states [8]. Consequently, this section reviews the literature across two aspects: trajectory-based monitoring of earthmoving operations and activity recognition methods for inferring semantic states.

2.1 Trajectory-based Earthmoving Operation Monitoring

Tracking construction equipment using Global Positioning System (GPS) has been widely investigated to support productivity analysis and operational monitoring. GPS-based systems are extensively applied to capture the spatiotemporal movement of earthmoving equipment, enabling the inference of critical operational patterns, such as cycle times, travel distances, and equipment utilization [9,10]. With the advent of RTK-GNSS, the positioning accuracy of these systems has improved significantly, making trajectory data increasingly suitable for detailed analysis of equipment behavior on construction sites [4].

Recent studies have further explored data-driven and machine learning–based approaches to extract higher-level semantic information from equipment trajectories and sensor data. By leveraging supervised learning, probabilistic models, or deep learning techniques, these methods aim to recognize equipment activities or operational states [10,11], which have demonstrated promising classification accuracy under controlled conditions and highlight the potential of learning-based models for capturing complex motion patterns.

However, inferring detailed equipment activities solely from trajectory data remains challenging. Several studies have attempted to identify activities using speed thresholds or proximity-based rules. While these rule-based methods are computationally efficient and easy to implement, they lack robustness in complex scenarios.

In congested and dynamic construction environments, equipment frequently operates at low speeds, performs short repositioning movements, or temporarily pauses within active zones due to traffic or delays. Consequently, purely kinematic-based approaches often struggle to distinguish between functionally distinct states, leading to noisy state transitions and misclassification. These limitations highlight the critical need for activity recognition methods that account for the cyclic and sequential logic of earthmoving operations, rather than relying exclusively on instantaneous spatial or kinematic threshold rules.

2.2 Activity Recognition Approaches for Construction Equipment

Automated activity recognition serves as the analytical core for evaluating construction productivity and emissions. By analyzing spatiotemporal data, researchers can infer operational patterns at a high level, such as cycle times, haul distances, and overall equipment utilization rates. The integration of high-precision RTK-GNSS has further refined this capability, allowing for the detection of subtle changes based on positioning data.

Armin et al. [11] categorized existing approaches of equipment activity recognition based on their input data sources, including vision-based, audio-based, and motion-based methods. Vision-based approaches rely on camera data and have demonstrated high accuracy, but are sensitive to lighting conditions, occlusions, and site complexity. Audio-based methods utilize acoustic signals and can be cost-effective, but their performance may vary depending on environmental noise. Motion-based approaches, which use trajectory and kinematic data from sensors (e.g., GPS, IMU, or UWB), are more robust to environmental conditions and are well suited for large-scale outdoor construction sites.

However, they require effective modeling of temporal dynamics to infer meaningful activity states from raw motion data. Translating raw kinematic data into semantic activity states remains a complex challenge. Existing methodologies can be broadly categorized into heuristic rule-based approaches [12], classical machine learning methods (e.g., Support Vector Machines [13, 14], Random Forests [15]), and deep learning models (e.g., LSTM [16], CNN [17]). Heuristic rule-based methods infer activities using predefined heuristics, such as speed thresholds or geofence-based proximity rules. These methods are favored for their low computational cost and ease of deployment. But they often lack flexibility in handling complex and irregular operational patterns. In contrast, classical machine learning methods can learn complex patterns from multi-sensor data (e.g., fusing location data with accelerometers), aiming to improve classification accuracy for complex maneuvers [6, 11]. While they improve classification performance over purely heuristic approaches, they typically rely on carefully designed features and overlook temporal dependencies. Deep learning models further enhance classification capability by learning features directly from raw or minimally processed data. However, these methods require substantial labeled data and often lack interpretability, which limits their practical deployment in construction environments.

All these methods have inherent limitations in dynamic site environments. Machine learning models often suffer from overfitting and lack explainability. On the other hand, purely rule-based approaches are often too rigid. In congested sites, equipment frequently exhibits irregular movement patterns, such as creeping at low speeds due to traffic or performing short repositioning maneuvers, which do not align with static kinematic thresholds. This underscores the necessity for a method that explicitly accounts for the cyclic, sequential nature of earthmoving operations.

In this context, FSM-based approach can be viewed as a structured modeling framework within motion-based methods, explicitly incorporating state-transition logic to improve temporal consistency while maintaining interpretability. Compared with rule-based methods that rely on isolated heuristics, FSM-based approaches explicitly model temporal state transitions for more consistent activity interpretation, while remaining more interpretable and data-efficient than machine learning-based methods.

3 Methods

This section describes the proposed trajectory-based activity recognition method for earthmoving operations. The method integrates RTK-GNSS trajectory data with FSM to infer temporally consistent equipment activity states. The overall workflow consists of trajectory preprocessing, FSM-based state modeling, rule-based candidate state detection, and activity timeline generation. Figure 1 illustrates the overall workflow of the proposed trajectory-based FSM approach for equipment activity recognition.

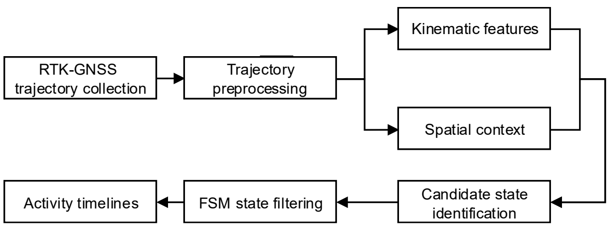

Figure 1. Overview of the trajectory-based FSM workflow for equipment activity recognition in earthmoving operations.

3.1 Trajectory Data Acquisition and Preprocessing

To capture the precise movement patterns of the fleet, equipment trajectories are collected using RTK-GNSS sensors mounted on excavators and dump trucks. These sensors record positioning data, including latitude, longitude, and heading, at a frequency of 1 Hz. Since raw coordinates lack operational context, they are transformed into a site-aligned local coordinate system that matches the digital site layout. This alignment enables the system to perform spatial reasoning, automatically determining whether a machine is located within specific operational zones such as excavation pits, loading points, dumping areas, or haul roads.

From the processed trajectories, two fundamental kinematic features are derived to describe equipment behavior: translational speed and rotational velocity. Translational speed is primarily used to distinguish between stationary states (e.g., *Load*, *Idle*) and mobile states (e.g., *Haul*, *Return*). Meanwhile, rotational velocity, calculated from the change in heading, is a critical indicator for identifying excavator cycles, as these machines frequently rotate their upper structure while the tracks remain static during digging and swinging operations.

However, raw field data inevitably contains noise due to signal multipath effects or temporary obstructions. To prevent the activity recognition model from reacting to these false fluctuations, a temporal smoothing filter is applied to the kinematic data streams. This preprocessing step reduces short-term jitter and satellite signal drift, ensuring that the inputs for the FSM are stable and reliable.

3.2 FSM Design for Earthmoving Equipment

To capture the cyclic workflows of earthmoving operations, separate FSMs are designed for excavators and dump trucks, as illustrated in Figure 2. The state identification integrates instantaneous kinematic features with spatial context. Candidate states are first proposed based on speed and heading, then validated against the equipment's location within defined operational zones (e.g., loading or dumping areas).

For dump trucks, the FSM defines states such as *Load, Haul, Dump, Return,* and *Wait*. Transitions are triggered by specific thresholds, for example, speeds above 2.0 m/s indicate driving modes, while low speeds in specific zones indicate service or queuing. For excavators, the *Excavating* state is distinctively identified by low translational speed ($v < 0.5\ m/s$) combined with high rotational velocity ($\omega > 5\ °/s$).

The FSM enforces predecessor logic to maintain temporal consistency. By explicitly coding allowable transition sequences, such as preventing a truck from entering *Load* without a preceding *Return* state, the system effectively filters out unrealistic state switches caused by signal noise or short interruptions, ensuring robust activity recognition.

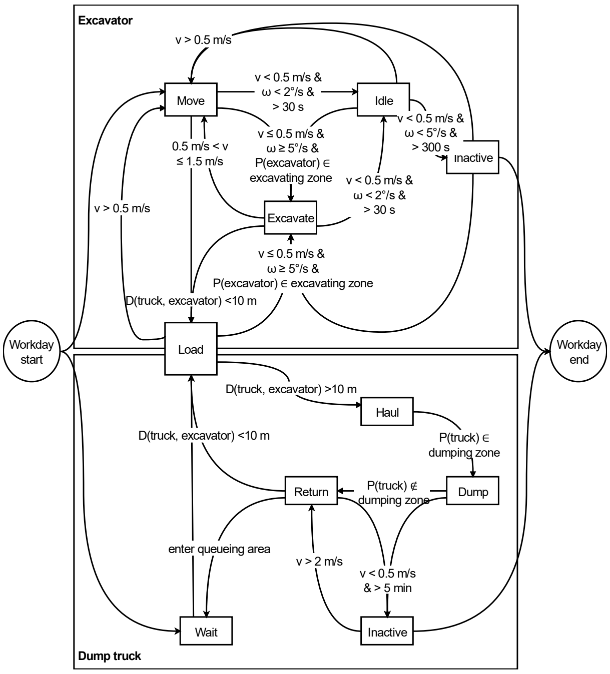

Figure 2. Finite-state machine for excavator and dump truck activity recognition. States (rectangles) and transitions (arrows) are determined by kinematic, spatial, and temporal conditions derived from RTK-GNSS trajectories.

3.3 Rule-based Candidate State Identification

At each discrete time step, candidate activity states are preliminarily identified by evaluating instantaneous kinematic features against predefined thresholds. The primary differentiator is translational speed (v), which serves to classify equipment behavior into stationary, low-speed maneuvering, or high-speed hauling modes. For instance, a speed threshold of 0.5 m/s is selected to distinguish productive stationary activities, such as *Load* and *Dump*, from active transport, while speeds exceeding 2.0 m/s generally indicate a driving state. However, kinematic data alone is often insufficient to determine a stationary state; for example, a truck stops due to traffic looks identical to one stopping for loading. Therefore, spatial constraints are applied as a necessary secondary filter to resolve these ambiguities.

For dump trucks, the identification logic relies heavily on geofenced operational zones to interpret low-speed behaviors. Specifically, a low-speed condition ($v < 0.5\ m/s$) is mapped to a specific activity based on the equipment's containment within defined areas: if the truck is located within an excavator's loading radius (10 m), the state is identified as *Load*; if it is within a designated dumping zone, it is labeled as *Dump*; and if positioned in a queueing area, it is classified as *Wait*. Conversely, high-speed driving periods are categorized into *Haul* or *Return* depending on the truck's position within the haul corridors and its direction of travel relative to the excavation zones. The detailed rule set for dump trucks is summarized in Table 1.

Table 1. State identification rules for dump trucks.

State	Kinematic condition	Spatial condition	Predecessor
Load	v ≤ 0.5 m/s	Distance to excavator ≤ 10 m	*Wait*, *Return*
Dump	v ≤ 0.5 m/s	Within dumping zone	*Haul*
Haul	v ≥ 2.0 m/s	Along haul corridor	*Load*
Return	v ≥ 2.0 m/s	Along return corridor	*Dump*
Wait	v < 0.5 m/s	Within queue area	Duration ≥ 30 s
Inactive	v < 0.2 m/s	Anywhere	Duration ≥ 300 s

Excavators require a more complex rule set due to their stationary working nature, where the chassis remains fixed while the upper structure performs the work. Consequently, rotational velocity becomes a critical indicator alongside translational speed. A combination of low translational speed (($v < 0.5\ m/s$) and significant upper-structure rotation ($\omega > 5\ °/s$) within the excavation zone is defined as the *Excavate* state. When it is in close proximity to a dump truck, it is reclassified as *Load*. Repositioning movements are captured when the translational speed falls between 0.5 and 1.5 m/s. Finally, prolonged periods of low motion, both in translation and rotation, are categorized as *Idling* or *Inactive* based on specific duration thresholds, as detailed in Table 2.

The threshold values used in the rule-based candidate state identification were determined based on a combination of domain knowledge, exploratory analysis of the collected trajectory data, and iterative calibration. Specifically, speed thresholds were selected to distinguish between stationary, low-speed maneuvering, and active hauling states observed in the dataset. The rotational velocity threshold reflects typical excavator swing behavior during excavation. The spatial threshold (e.g., 10 m radius) corresponds to practical interaction distances between excavators and dump trucks on site. Duration thresholds were introduced to differentiate short-term pauses from prolonged inactivity.

These parameters can be iteratively refined to ensure temporally consistent activity transitions while avoiding excessive sensitivity to noise in the trajectory data. In practice, moderate variations in these thresholds were found to have limited impact on the overall cyclic activity patterns. These rules generate a set of candidate states that represent plausible equipment activities at each timestep but may still contain short-term inconsistencies.

Table 2. State identification rules for excavators.

State	Kinematic condition	Spatial condition	Predecessor
Load	$v \leq 0.5$ m/s	Distance to truck ≤ 10 m	*Move, Excavate*
Excavate	$v \leq 0.5$ m/s $\omega > 5°$ /s	Within excavating zone	*Move, Load*
Move	$0.5 < v \leq 1.5$ m/s	Anywhere	*Excavate, Load*
Idle	$v \leq 0.5$ m/s $\omega \leq 2°$ /s	Anywhere	Duration > 30 s
Inactive	$v \leq 0.5$ m/s $\omega \leq 2°$ /s	Anywhere	Duration > 300 s

3.4 FSM-Based State Filtering and Activity Timeline Generation

The candidate states are filtered through the FSM transition rules to ensure temporal consistency. Only transitions that are allowed by the FSM are accepted, while invalid transitions are rejected or delayed until valid conditions are satisfied. This process prevents rapid switching between states caused by measurement noise, brief pauses, or short repositioning movements.

The final output of the method is a continuous activity timeline for each equipment unit, describing the sequence and duration of operational states over time. These timelines capture the cyclic structure of earthmoving operations and enable quantitative analysis of duty cycles, utilization, queueing behavior, and non-productive time.

The proposed FSM-based trajectory-driven method provides an interpretable solution for equipment activity recognition in earthmoving operations. By combining kinematic features, spatial context, and FSM-based temporal constraints, the method connects raw trajectory data and semantic operational states. The resulting activity timelines can be directly integrated into downstream applications, such as performance analysis and simulation of earthmoving operations.

4 Case Study and Results

The proposed trajectory-based activity recognition method was evaluated using data collected from a real-world earthmoving operation. The case study involves excavation and hauling activities carried out on an active construction site, where multiple excavators and dump trucks operated simultaneously within a confined workspace.

The study area includes predefined operational zones such as excavation areas, loading zones, dumping areas, haul corridors, return paths, and queueing areas. These zones were derived from the site layout and used to provide spatial context for activity recognition. Trajectory data from one representative workday were selected for analysis to capture typical operational patterns while avoiding interruptions caused by weather or major schedule changes. Figure 3 illustrates the spatial distribution of tracked equipment trajectories overlaid on the site layout and orthophoto.

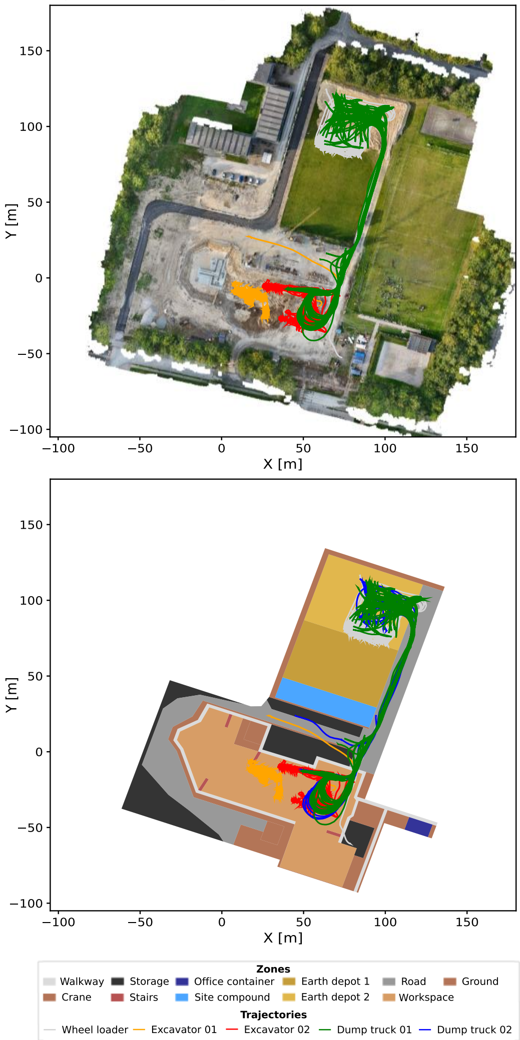

Figure 3. Trajectories of tracked equipment against the 2D site layout (upper image) and orthophoto (lower image) for one workday.

To distinguish the semantic activities visually, Figure 4 shows the typical dumper duty cycle observed from on-site drone images, illustrating the dump trucks' states of *Load*, *Haul*, *Dump*, *Return*, and *Wait* that the algorithm aims to identify.

Figure 4. Observed dump truck duty cycle: (a) Load, (b) Haul, (c) Dump, (d) Return, and (e) Wait.

4.1 Activity Recognition Results

The FSM-based activity recognition method was applied to the processed RTK-GNSS trajectories to infer equipment activity states over time. For each excavator and dump truck, the method generated a continuous activity timeline describing the sequence and duration of operational states. Figure 5 presents the identified activity timelines for the tracked equipment on the selected workday. The results show clear cyclic patterns consistent with typical earthmoving operations, dump trucks alternate between loading at the excavation area, hauling material to the dumping location, dumping, and returning to the excavation site. Compared with simple rule-based classification, the FSM-based approach produces temporally consistent state sequences without rapid fluctuations. Short interruptions, low-speed maneuvers, and brief pauses within operational zones are effectively filtered out by the FSM transition logic.

To quantitatively validate the FSM method, we established a rigorous second-by-second ground truth by manually annotating one hours of synchronized video footage as the upper diagram shown in Figure 5, where two dumpers worked in parallel.

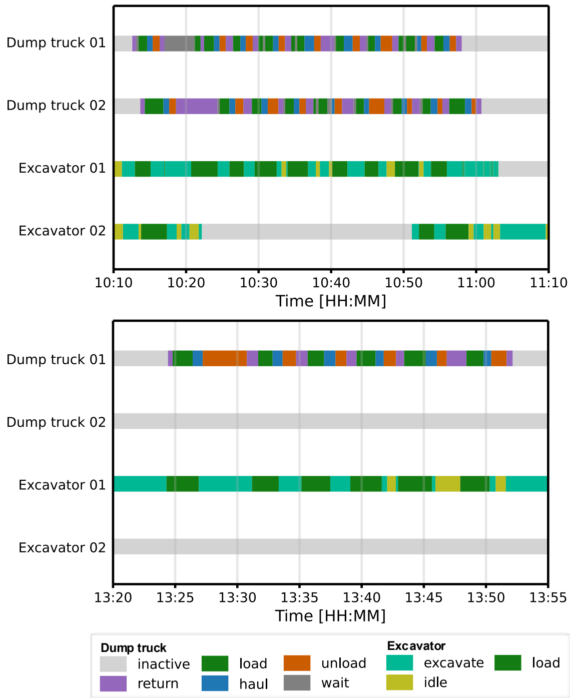

Figure 5. Timeline of identified working stages of the excavators and trucks on one selected working day.

To account for these natural phase shifts without unfairly penalizing the model, we evaluated the recognition accuracy using a standard point-by-point metric with a ± 10-second temporal tolerance window. As detailed in Table 3, the FSM approach demonstrates exceptional reliability for key duty cycle activities. It achieved a satisfying Recall and an outstanding F1-Score of 1.00 for Unload, combined with a high Precision of 0.90 for Haul. The high performance for Unload is mainly due to its clear spatial constraint, as it is defined within a fixed dumping zone. In contrast, other activities depend more on the relative positioning and interactions with excavators, and are more susceptible to interference from surrounding equipment, which introduces ambiguity and leads to comparatively lower performance.

Table 3. Quantitative evaluation of FSM-based activity recognition for dumpers against manual annotation.

Activity	Precision	Recall	F1-Score
Load	1.00	0.39	0.56
Haul	0.90	0.51	0.66
Unload	1.00	1.00	1.00
Return	0.61	0.95	0.74
Wait	0.56	0.59	0.58

4.2 Analysis of Operational Patterns

The extracted activity timelines enable quantitative analysis of equipment duty cycles and interaction patterns. For dump trucks, a substantial portion of non-productive time is associated with waiting and idling near the excavation area, reflecting queue formation when multiple trucks compete for limited excavator capacity. These queueing periods can be distinguished from active loading and hauling states due to the integration of spatial constraints and predecessor logic in the FSM.

For excavators, the activity timelines reveal dominant *Excavate* and *Load* states, with idling primarily occurring during periods of truck unavailability or short operational interruptions. The temporal alignment between excavator *Load* states and truck *Load* states further confirms the consistency of the identified interactions between equipment units.

For this specific analysis, the study focuses on the utilization rate of the dump trucks because the on-site excavators were intermittently tasked with loading external trucks, which introduces variability to the excavator's operation independent of the tracked trucks. Table 4 summarizes the observed work statistics for the selected workday. It presents the total duration and percentage of "Work" (active states: Load, Haul, Dump, Return) vs. "Idle" (Wait) for the monitored equipment.

Table 4. Summary of working cycles of two trucks on one selected workday.

Machine	Work (min)	Idle (min)	Utilization (%)
Truck 01	238.16	11.67	95.33
Truck 02	114.45	29.10	79.73

Overall, the case study confirms that the trajectory-based FSM approach can robustly infer meaningful activity states from RTK-GNSS data under realistic site conditions. The resulting activity timelines provide a representation of earthmoving operations, forming a reliable foundation for future applications such as performance analysis and bottleneck identification.

5 Discussion

This study demonstrates that the FSM-based approach provides an effective and interpretable approach for recognizing equipment activity states from RTK-GNSS trajectory data in earthmoving operations. As evidenced by our quantitative validation against a second-by-second manual ground truth, the algorithm reliably captures critical operational cycles, achieving perfect recall for unloading events and high precision (0.90) for hauling. Compared with simple rule-based methods that rely solely on instantaneous thresholds, the FSM-based approach introduces temporal memory through predecessor constraints. This logic significantly reduces unrealistic state oscillations caused by GPS signal noise, short interruptions, or low-speed maneuvering. Furthermore, unlike data-driven classification models (e.g., neural networks), the FSM logic does not require substantial labeled training datasets and remains transparent to domain experts, allowing for easier debugging and adaptation to different site layouts.

Beyond activity recognition, the generated timelines provide critical insights into fleet performance. The case study revealed that operational inefficiencies can be quantified. As observed in the results, the overlap of truck waiting times highlights a temporary resource imbalance between the excavator's loading capacity and the truck fleet's arrival rate. By visualizing these hidden non-productive times, the proposed framework allows site managers to move from reactive observations to proactive resource leveling, for instance, by adjusting the number of trucks to reduce idling.

Several limitations should be acknowledged. First, the method relies on predefined spatial zones and threshold parameters, which currently require site-specific tuning based on the site layout. Second, equipment performing side tasks or operating outside predefined workflows may lead to temporary misclassification. These limitations could be addressed by incorporating additional sensing modalities to provide complementary information [7, 18]. Nevertheless, the current approach achieves a practical balance between robustness, interpretability, and deployment effort for outdoor earthmoving environments.

6 Conclusions

This paper presented a robust trajectory-based activity recognition method for earthmoving operations using finite-state machines. By integrating RTK-GNSS trajectory data with kinematic features, spatial context, and predecessor constraints, the proposed method infers temporally consistent activity states of excavators and dump trucks. Validation in a real-world tunnel construction project demonstrated that the method effectively captures cyclic operational patterns and produces interpretable activity timelines under realistic site conditions.

The contributions of this study extend beyond algorithm development. By transforming raw position data into semantic operational metrics, the framework provides a reliable foundation for Digital Twin applications. It enables project managers to pinpoint bottlenecks in near real-time and make informed decisions regarding process optimization.

Future research will focus on automating the generation of site maps and geofences to reduce manual setup time. Additionally, we aim to integrate the output of this productivity analysis into real-time simulation models to predict future project performance and enable proactive schedule adjustments.

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