ABSTRACT

Demolition operations constitute one of the most complex and variability-sensitive phases of the construction lifecycle, characterized by dynamic structural instability, heterogeneous debris compositions, continuously evolving spatial constraints, and strong dependence on operator expertise. While excavator guidance systems have been widely studied for earthwork applications, most existing frameworks address isolated dimensions of guidance, such as machine kinematics or geometric positioning, without integrating the multidimensional decision requirements inherent to demolition environments. This fragmentation limits their ability to provide synchronized, context-aware decision support capable of reducing operator-dependent variability, improving productivity, and enhancing material recoverability.

This dissertation proposes and validates a demolition-specific, three-dimensional excavator guidance system framework that integrates task-related, machine-related, and worksite-related information within a unified operational architecture. The research begins with a systematic literature synthesis that reconceptualizes excavator guidance as an information-centric problem and establishes a structured knowledge base defining the informational and modeling components required for effective guidance. Rather than treating guidance systems as collections of sensors or isolated algorithms, the study formalizes guidance as an interdependent information architecture composed of task intent, machine motion dynamics, and worksite awareness. This analysis clarifies how guidance must adapt across demolition activity cycles and reveals the absence of synchronized multidimensional integration in prior work, establishing the conceptual foundation for the proposed three-dimensional guidance paradigm.

Building upon this conceptual foundation, a synchronized multimodal perception architecture is developed to reconstruct demolition operations as unified operational-state tuples. The perception backbone integrates (i) kinematics-based machine-state reconstruction using inertial measurement units and Denavit–Hartenberg formulation, (ii) hierarchical task-state segmentation through deterministic rule-based modeling, (iii) self-supervised material representation and clustering for debris characterization, and (iv) LiDAR–RGB fusion–based three-dimensional worksite reconstruction. These components are temporally aligned through timestamp-driven

synchronization, producing coherent, multi-layer operational states suitable for prescriptive reasoning.

Leveraging the reconstructed states, the study develops an AI-driven, multidimensional guidance framework that generates coordinated prescriptive outputs across task sequencing, spatial routing, and micro-movement execution. Supervised learning models predict next activities, material categories, dump-zone assignments, and navigation directions, while a movement-pattern clustering and classification strategy prescribes optimal joint-level execution patterns. A performance-refined training strategy is incorporated to ensure that learned decision logic reflects efficiency-consistent behavior rather than statistical frequency alone. Model validation combines classification diagnostics with nonparametric and Monte Carlo–based hypothesis testing to verify predictive reliability and behavioral alignment with high-performance executions.

The operational effectiveness of the framework is experimentally evaluated using a controlled demolition-sorting testbed with synchronized multimodal data collected from multiple operators. Four guidance configurations—Baseline (no guidance), 1D machine-level guidance, 2D task–site guidance, and fully integrated 3D guidance—are compared using a distribution-robust statistical validation strategy. Regime-based Gaussian mixture modeling isolates high-performance coordination states, while stochastic dominance analysis, effect-size estimation, bootstrap confidence intervals, and permutation testing assess probabilistic productivity improvements. Results demonstrate systematic and progressive performance improvements as informational dimensionality increases, with fully integrated guidance producing the strongest structural enhancement. Furthermore, structural skill-gap compression analysis using Hodges–Lehmann estimation and near-parity probability metrics reveals that 3D guidance reduces performance disparities and promotes convergence toward elite-level coordination behavior.

Collectively, this research establishes a theoretically grounded, methodologically integrated, and empirically validated framework for demolition-specific excavator guidance. By synchronizing perception, multidimensional decision modeling, and statistically rigorous validation within a unified architecture, the dissertation advances the state of knowledge in intelligent construction systems and demonstrates that structured integration of task, machine, and worksite information can transform operator performance under dynamic demolition conditions.