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Virtual-physical digital twin testbed for heterogeneous crowd operations

Mingliang XU[1,2,3], Zheng WANG[1], Yang MENG[1], Wencan LUO[1], Hua WANG[1,2,3*], Shuo HE[1,2,3], Chaochao LI[1,2,3], Yibo GUO[1,2,3], Yafei LI[1,2,3] & Pei LV[1,2,3]

[1] *School of Computer Science and Artificial Intelligence, Zhengzhou University, Zhengzhou 450001, China*
[2] *Engineering Research Center of Intelligent Swarm Systems, Ministry of Education, Zhengzhou 450001, China*
[3] *National Supercomputing Center in Zhengzhou, Zhengzhou 450001, China*

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Heterogeneous crowd operations involve complex procedural subtasks performed by dynamic teams with diverse agent behaviors, tailored to specific task requirements. Examples of such operations include carrier aircraft support, airport ground handling, and logistics transport. Using a hybrid virtual-physical digital twin testbed for scenario generation and plan verification in heterogeneous crowd operations addresses the issues of low credibility in virtual simulations and the high costs associated with real-world testing. It is becoming increasingly important in practical applications.

In recent years, the development of technologies such as artificial intelligence and the Internet of Things has brought widespread attention to digital twin testbeds, which have made significant strides in fields such as workshop production, rail transportation, power systems, and urban traffic. Among these, the traffic digital twin testbed is particularly relevant to crowd operations. Current traffic digital twin testbeds focus on analyzing real-time data from the physical world to enhance predictive capabilities [1, 2]. Virtual vehicles in these systems typically replicate real-world environments, which heavily rely on physical contexts. Meanwhile, the potential of simulated agents has not been fully explored. To address these challenges, Dong et al. [3] designed a virtual-physical hybrid digital twin testbed for agent motion based on physical sand table simulation, offering a practical means to validate agent movements in road networks. However, in this testbed, agents within the physical sand table cannot detect those in the virtual sand table, necessitating centralized control of all agent behaviors in the cloud. This makes it difficult to simulate diverse behaviors of heterogeneous crowds [2]. Additionally, the testbed does not consider complex operational tasks, making it unsuitable for simulating dynamic teams directly. Existing crowd simulation platforms, such as AnyLogic[1)] and NetLogo[2)], do offer some task-oriented crowd operation modeling. However, they primarily focus on simple operational tasks and have not yet supported the modeling of dynamic teams with dynamic coupling relationships.

To address the above issues, we introduce an ontology semantic model that characterizes the heterogeneous crowd operations with dynamic teams in complex operational tasks. We then design a virtual-physical digital twin testbed upon this model to simulate heterogeneous crowd operations.

Ontology semantic model of heterogeneous crowd operations. Flexible and controllable ontological semantic representation is crucial for supporting complex and dynamic task simulation. Here, we first decouple heterogeneous crowd operations into simple operational elements using complex systems theory, and then perform hierarchical division and ontological semantic representation (Figure 1(a)). Specifically, it includes as following.

- Element layer. Includes all elements in the operational task, such as personnel, vehicles, materials, tools, and facilities. Each element contains a set of members belonging to the element class. For example, the facility ontology includes equipment and buildings used for specific purposes or functions, such as gas stations and elevators.
- Team layer. Aggregates the element layer ontologies into different teams based on task allocation. Different teams have different numbers of operational agents. A single operational agent can form a team. Additionally, an agent can belong to multiple teams.
- Subtask layer. Includes the operational teams required to complete the subtask and describe the goal-directed guidance and crowd collaboration within the team. For example, quality control checks in takeoff operations, retrieving the fuel nozzle in refueling operations, and unloading in transfer operations are typical subtasks.
- Task layer. Includes a series of subtask ontologies.

* Corresponding author (email: iewanghua@zzu.edu.cn)
1) AnyLogic. https://www.anylogic.com/.
2) NetLogo. https://ccl.northwestern.edu/netlogo/.

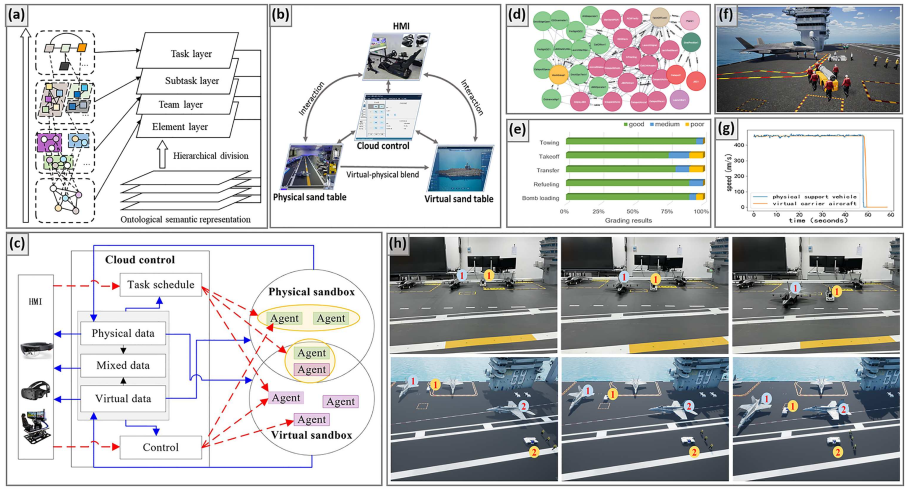

Figure 1 (Color online) (a) The ontology semantic representation of heterogeneous crowd operations. (b) The schematic of our digital twin testbed illustrated by carrier aircraft support operations. The physical sand table has a 1 : 20 ratio with respect to the real aircraft carrier. (c) The architecture of our digital twin testbed. The solid blue arrows indicate the data flow, while the dashed red arrows represent feedback commands. Agents enclosed in green boxes represent physical agents, those in purple boxes represent virtual agents, and agents within yellow ellipses represent task teams. (d) Knowledge graph of the takeoff task based on the ontology semantic model. (e) The results of the user study on task interaction and orchestration functionality. (f) A snapshot depicting the transfer task. (g) The changing speed relationship between a physical vehicle and a virtual aircraft towed by it. (h) Simulation snapshots featuring coupling team behaviors of physical/virtual aircraft, physical/virtual vehicles, and virtual personnel.

Tasks follow a predefined process, where different subtasks must be connected in a specific order to ensure the successful completion of the task. Typical tasks include takeoff, refueling, and transfer operations.

This ontology model provides a semantic foundation for generating operations involving complex procedural subtasks and dynamic teams.

Virtual-physical digital twin testbed for heterogeneous crowd operations. The schematic of our testbed is shown in Figure 1(b). It comprises four modules: cloud control, physical sand table, virtual sand table and human-machine interface (HMI).

• Cloud control. The cloud control acts as the central hub of the testbed, providing a comprehensive overview of the virtual-physical integrated digital twin testbed. It is responsible for real-time data aggregation, including the collection, fusion, and alignment across the entire virtual and physical environment. Additionally, it handles task assignment, which involves scheduling, configuration, and allocation to virtual and physical operation teams. Furthermore, it controls the movement of both virtual and physical agents.

• Physical sand table. The physical sand table provides a scaled real-world test environment. It is created by proportionally scaling and replicating the actual environment to reflect real-world operational conditions. It consists of three primary components: the physical environment, physical operational agents, and data capture modules. Each physical operational agent is integrated with a path planning component and a behavior control component to enable diverse behaviors of heterogeneous crowds.

• Virtual sand table. The virtual sand table offers a flexible design for the quantity, motion behavior and dynamics of crowds. It is developed based on a digital replica of the physical sand table, ensuring consistency with real-world scales. It is embedded with a crowd simulation engine that utilizes the high level architecture (HLA) framework. The engine includes components for path planning, heterogeneous crowd simulation dynamics, and scene setup, aimed at achieving diverse simulations of heterogeneous crowds.

• HMI. The HMI serves as a pivotal link connecting the cloud control, physical sand table, virtual sand table, and users. By utilizing HMI devices such as driving simulators and virtual/augmented reality headsets, the HMI module enables users to interactively engage in scenarios from the physical/virtual sand tables, as well as their combination, providing a first-person perspective for task assignment and command control.

Based on the aforementioned four modules, the testbed can simulate complex operations involving heterogeneous crowds. The architecture of the testbed is illustrated in Figure 1(c). The interactions among these four modules primarily manifest in data transmission and command feedback.

• Data transmission. As the central hub of the testbed, the cloud control module receives environmental data from the physical sand table via data capture devices. It then fuses and completes the multi-source data using techniques such as Kalman filtering and panoramic stitching, resulting in comprehensive physical data. Environmental data from the virtual sand table is synchronized and uploaded to the cloud control module according to the virtual simulation frequency, resulting in virtual data. The cloud control module then aligns both types of data to obtain mixed data, which integrates the virtual and physical environments. These three types of data are available to all four modules of the testbed for their use. Specifically, for the cloud control module, the scheduling of crowd tasks requires a God's-eye view of the entire scene, i.e., mixed data. Controlling the virtual and physical agents in the tasks requires environmental data. Different control requirements necessitate different data, including the local field of view of the task agent and all data from the elements within the task. This data is also included in the mixed data. For the HMI module, we provide different data to different HMI devices. For instance, we provide physical data and mixed data to HoloLens, mixed data and virtual data to HTC Vive, and all three types of data to the driving simulator. In the case of the virtual sand table, the cloud control module synchronizes the aligned physical data to the virtual sand table according to the virtual simulation frequency, enabling the task agents within the virtual sand table to make appropriate behavioral decisions. For the physical sand table, the sensors of the physical agents are unable to detect the presence of virtual agents. High-frequency data transmission from the cloud control module can be impacted by network communication issues, complicating real-time decision-making by the task agents. To minimize network communication, we adopt a risk prediction-based shared control method. It involves constructing a composite risk field by overlaying a static risk field formed by static obstacles around the physical object and a dynamic risk field formed by dynamic obstacles in the cloud. When the risk reaches a certain threshold, a risk alert is triggered, initiating cloud control. Otherwise, the physical agents make autonomous decisions based on the information perceived by their own sensors.

• Command feedback. In terms of command feedback, the task scheduling and control components within the cloud control module are responsible for generating and managing feedback. These components can generate corresponding feedback commands based on physical, virtual, or mixed data, and can also collect feedback commands submitted via the HMI module. Subsequently, these commands are sent to the virtual and physical environments. The task scheduling component can assign tasks to individual or team task agents in either the virtual or physical environment as needed. The control component primarily manages individual task agents in these environments.

Results. To validate the efficacy of the testbed, carrier aircraft support operations are chosen as a case study to evaluate its ability to handle complex operational tasks, diverse crowd behaviors and dynamic team modeling.

In our ontology semantic model, the task layer encompasses 7 primary tasks: takeoff, recovery, transfer, towing, refueling, bomb loading, and firefighting. The subtask layer consists of 55 specific subtasks, while the element layer includes 653 distinct types of elements. The number of team types in the team layer is dynamically generated according to operational requirements. The concepts and relationships within this ontology model are extracted using natural language processing techniques from publicly available documents and subsequently validated by domain experts. Finally, this data is stored in the form of a knowledge graph. Figure 1(d) presents a segment of the knowledge graph for the takeoff task. This data enables users to interactively orchestrate tasks, subtasks, and team behaviors to generate complex tasks, which ultimately manifest on the testbed as diverse crowd behaviors and dynamic team behaviors, such as changes in the number of operational agents within the team and changes in their states.

The feature of the testbed in complex task modeling is embodied in its orchestration of complex tasks, which is challenging to quantify. Here we conduct a user study by sharing the testbed's task interaction and orchestration functionality. We chose 20 individuals who have a basic understanding of carrier aircraft support operations (having participated in related project developments) to assess the testbed's orchestration capabilities in five tasks: takeoff, transfer, towing, refueling and bomb loading. Figure 1(f) provides a snapshot of a transfer task. Participants rated their experience with orchestrating each task on a scale of three levels: good, medium, and poor. The results are shown in Figure 1(e). It can be seen that the testbed receives acknowledgment for its ability to orchestrate the complex tasks involved in support operations.

The feature of the testbed in diverse crowd behaviors and dynamic team modeling is demonstrated through its robust data transmission and command feedback architecture. This architecture enables the modeling of a wide range of crowd behaviors via decentralized calls to various crowd models, accommodating individual dynamics, coupling dynamics, and hybrid virtual-physical agents. Figure 1(g) illustrates the changing speed relationship between a physical vehicle and a virtual aircraft in a towing scenario where the vehicle tows the aircraft. It is evident that the virtual aircraft closely tracks the physical vehicle. Changes in the vehicle's motion state prompt corresponding adjustments in the virtual aircraft, demonstrating the testbed's capability to simulate dynamic teams with dynamic coupling relationships when the state of one team agent changes. Figure 1(h) shows snapshots of task scenarios involving real aircraft, real vehicles, as well as virtual aircraft, virtual vehicles, and virtual personnel. This shows the testbed's ability to simulate dynamic team behaviors in heterogeneous crowds.

Conclusion and limitations. Our testbed provides users with a twin model that supports the configuration of various complex team tasks through ontological semantics. It also offers an interaction architecture among the testbed's four modules to facilitate rich data transmission and command feedback. The integration of diverse components within each virtual/physical agent, combined with these features, enables users to freely configure the control of crowd agents. For example, users can implement centralized control for optimal objectives (where control commands are issued from the cloud control module) or decentralized control to achieve rich heterogeneous individual behaviors (where environmental data is downloaded from the cloud control module and the virtual/physical agents make control decisions independently).

However, the testbed has certain limitations. First, the miniature agents on the physical sand table exhibit performance bottlenecks, and the simulated task processes do not fully align with real-world scenarios. Second, the algorithmic components integrated into the testbed are based on existing technologies, which struggle to accurately simulate the rich behaviors among heterogeneous agents during crowd operations. In the future, we plan to optimize the relevant software and hardware components using the initial data collected from the testbed.

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Supporting information Videos and other supplemental documents. The supporting information is available online at info.scichina.com and link.springer.com. The supporting materials are published as submitted, without typesetting or editing. The responsibility for scientific accuracy and content remains entirely with the authors.

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