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Research on Digital Twin System Platform Framework and Key Technologies of Unmanned Ground Equipment

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Abstract: As an emerging technology, digital twin is expected to bring novel application modes to the whole life cycle process of unmanned ground equipment, including research and development, design, control optimization, operation and maintenance, etc. The highly dynamic, complex, and uncertain characteristics of unmanned ground equipment and the battlefield environment also pose new challenges for digital twin technology. Starting from the new challenges faced by the digital twin of unmanned ground equipment, this paper designs a service-oriented cloud-edge-end collaborative platform architecture of the digital twin system of unmanned ground equipment, and further analyzes several key technologies supporting the implementation of the platform architecture.

Key words: unmanned ground equipment; digital twin; native cloud platform; Modeling and Simulation (M&S); artificial intelligence

1 Introduction

The future war will evolve in the direction of unmanned and intelligent, and a large number of unmanned equipment will be put into use in the battlefield, which will bring profound changes to the future combat mode. Using ubiquitous communication network to connect unmanned equipment to a unified combat cloud platform in real time can effectively promote the realization of new strategic tactics such as battlefield global perception, real-time intelligent decision-making, multi-service wide-area cooperative combat, and unmanned cluster distributed combat. At present, countries are also actively promoting the development of various types of unmanned equipment such as Unmanned Ground Vehicle (UGV), aerial drones, offshore unmanned boats, and underwater unmanned equipment. Actually, UGV is a kind of Unmanned Ground Equipment (UGE), except which UGE still includes various of unmanned ground robots or complex mechanical and electrical equipment. UGE is an important unmanned combat force deployed on the ground battlefield. The research and development of UGE is more difficult than other unmanned equipment, because the ground environment is more complex than the sea or air, where the unmanned equipment needs to have strong all-terrain adaptability. At present, most of the ground unmanned combat equipment requires soldiers to control through the terminal, and the level of intelligence and autonomy is relatively low. How to develop and design high-performance autonomous UGE that adapts to battlefield changes, and verify its combat capability efficiently and quickly, so that it can quickly deploy troops and give full play to its potential is an important technical issue that all countries are concerned about.

In recent years, digital twin has been widely discussed as an emerging hot topic. Starting with the digital twin of the manufacturing industry, followed by medical, energy, defense and others, a new wave of

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digital twins has also been set off. For the definition of digital twin, different industries and institutions are slightly different. Actually, digital twin refers to the digital model, which can evolve dynamically in real time to represent the physical entity credibly. The application based on digital twin refers to a series of activities carried out by using digital twin to feed back to physical asset, such as state monitoring based on digital twin, fault diagnosis based on digital twin, predictive control based on digital twin, decision support based on digital twin, etc. With the rapid development of Modeling and Simulation (M&S) technology, sensing technology, Internet of Things technology, communication technology, high-performance computing technology, and artificial intelligence technology, digital twin has gradually moved from the vision blueprint to the real world, and people are full of expectations for the industry innovation and disruptive development that digital twin will bring. As a new concept and technology, digital twin has aroused extensive discussion in the industry on how to enable the whole life cycle of the development, use, and maintenance of UGE.

Different from other equipment, the demand for flexibility and strong intelligence of UGE, the dynamic and uncertain characteristics of battlefield environment also bring new challenges to the digital twin technology of UGE.

(1) Faced with the challenges of the complexity and uncertainty from the battlefield environment. The battlefield environment is complex, including electromagnetic interference, enemy fire strike, and so on. The road condition fluctuates greatly and there are many occasional obstacles. Thus, UGE digital twin needs to use real-time multi-source sensing data to understand these changes. The battlefield situation is rapidly changing, and the dynamic and uncertain characteristics are prominent, which puts forward higher requirements for the rapid perception and intelligent cognitive ability of the digital twin.

(2) Faced with the frequent changes in the state of UGE and its vulnerability to severe challenges. In the service stage, due to the changes in the battlefield environment and the attack of the enemy, UGE may encounter different degrees of performance degradation and battle damage at any time. Digital twin needs real-time credible feedback of the real state of the equipment, which puts forward higher requirements for the dynamic interactivity and dynamic evolution of digital twin.

(3) Faced with the challenge of real-time decision-making of complex tasks. The battlefield situation is rapidly changing and complex. In many cases, the UGE needs to make real-time decisions considering the battlefield situation, process large volume of data, and computation in a short time, and obtain the optimal mission planning, which poses a challenge to the architecture and capabilities of the digital twin platform.

(4) Faced with the challenge of flexible configuration and fast deployment of different functional modules. For example, the transportation unmanned equipment can be quickly upgraded to the fire support unmanned equipment. The UGE also needs to have the ability of continuous self-learning. Its perception algorithm and control algorithm need to support online rapid upgrade, which also provides new challenges for the digital twin of UGE.

(5) Faced with the challenge of service-oriented ability to adapt to multiple needs. The UGE has different requirements for digital twin applications at different stages of the whole life cycle. It is necessary to design a service-oriented, customized, scalable, and extensible digital twin architecture to meet the needs of different departments for digital twins in different life cycle stages of unmanned equipment.

In order to effectively mitigate the aforementioned challenges, this paper proposes a UGE digital twin platform framework based on cloud-native technology and service-oriented design principles, and analyzes several key supporting technologies of digital twins from the perspective of model engineering. The proposed architecture and method leverage the advantages of cloud-edge collaborative computing, enabling the dynamic evolution of UGE digital twins, which helps represent real states of UGE credibly and support for rapid and accurate decision-making to address the complexities and uncertainties of changes on the battlefield. Leveraging cloud-native technologies, we can easily realize rapid and personalized construction, configuration, deployment, and updating of digital twin applications of UGE. So as to effectively meet the demands of UGE for multi-scenario personalized services and rapid adaptability capability on the battlefield.

2 Related Work

Joint Global Command and Control System (JADC2) is a new combat concept and plan for future wars proposed by the US Department of Defense in response to the opponent's anti-intervention and regional denial capabilities. The US Army's JADC2 strategy aims to integrate multi-domain combat forces of sea, land, air, and space to form a network, increase operational flexibility, and adapt to the requirements of distributed operations (mosaic warfare). It includes three core enabling technologies, artificial intelligence, combat cloud, and communication technology. The core is to establish the digital twin of the battlefield, virtualize each combat unit (equipment, even personnel) on the front line, and connect it to the combat cloud. With each combat unit, the sensor is connected to each shooter on the front line, and the combat forces are gathered quickly and flexibly to form a mesh killing chain, which effectively consumes and blocks the enemy. Digital twin technology is the core of JADC2 strategy. It uses a wide-area universal sensor system to establish a digital twin model of the battlefield. With the help of a new generation of artificial intelligence and machine learning technology, it can quickly capture key situation information from real-time massive battlefield ISR data, help commanders make rapid decisions, and quickly update combat plans and commands to any weapon equipment on the front line. Obviously, the star chain program that SpaceX is actively building will provide a solid communication foundation for the implementation of the JADC2 strategy. Its global, fast reconnaissance, surveillance, and communication relay capabilities will become a powerful tool for the US military to build a digital twin battlefield.

Michael Griffin, deputy secretary of Defense Research and Engineering, issued the "Department of Defense Digital Engineering Strategy" on 25 June 2018, which aims to guide the planning, development, and implementation of the entire Department of Defense digital engineering transformation. The strategy points out that digital technology has completely changed the business of most major industries and our personal life activities. By improving computing speed, storage capacity, and processing power, digital engineering has given a paradigm shift from the traditional "design-build-test" method to the "model-analysis-build" method. This approach allows the Department of Defense to build prototypes, conduct experiments and tests, support decisions and determine solutions in a virtual environment before delivering the project to combatants. And digital twin technology is incorporated into one of the supporting technologies of digital engineering strategy.

NVIDIA builds a twin environment of the city based on Omniverse's unmanned development platform, DRIVE Sim and DRIVE Map, which is used to develop and verify the ability of unmanned vehicle intelligent algorithms. The core is that the driverless scene can be reconstructed at any time according to the scenario, and the required sensor data can be obtained to optimize the driverless algorithm. NVIDIA twins the city's road network, including road details, and uses artificial intelligence. The method simulates the behavior of other vehicles at intersections or in extreme cases, and also establishes a database collected from real vehicle sensor data, such as on-board driving recorders.

In China, with the vigorous development of intelligent manufacturing, many experts and scholars have focused on the related concepts and technologies of digital twin, and many of them have begun to pay attention to the application of digital twin technology in the field of national defense. Among them, the concept of "parallel system" proposed by Zhang et al.[1] has many conceptual and technical similarities with the concept of digital twins. It emphasizes the integration and symbiosis of the virtual world and the physical world, and finally predicts and controls the actual system through the artificially constructed virtual system. Under the guidance of parallel system theory, domestic scholars have carried out related research on the application of parallel system in military system-of-systems combat training and parallel simulation[2]. In particular, the China Industry 4.0 Research Institute released the "Digital Twin Defense White Paper" in 2021, emphasizing the great application potential of digital twin as a disruptive technology in future defense, and summarizing three important research areas, the digital twin battlefield, digital twin equipment, and digital twin training. Reference [3] expounded the important progress made by the US military in the field of equipment digital twin in recent years, including ADT (fuselage digital twin), F35, and "Aegis" project, and pointed out that digital twin will be one of the core supporting technologies for future intelligent warfare.

In addition, domestic universities and research institutes represented by Beihang University and National University of Defense Technology have relevant research progress in the fields of unmanned equipment digital twin platform, digital twin battle damage assessment system, digital twin military deduction training, and etc.[3−11] Among them, Li et al.[4] proposed a five-layer macro framework for the application design of digital twin technology in the military field, which are the entity layer, the transmission layer, the data layer, the service layer, and the application layer. However, the implementation details and core technologies are not specific enough, and there is a lack of specific practice guidance for the digital twin platform of UGE. Song et al.[6] established a special digital twin platform for battlefield damage assessment. The reference platform highlights the dynamic interaction between the digital twin model and the physical equipment entity and the closed-loop optimization characteristics. It focuses on the data collection and analysis capabilities of the data layer and the analysis and decision-making capabilities of the application layer. However, due to the focus on the battle damage assessment scenario, the digital twin application scenarios of other UGE are not involved. In Ref. [7], a digital twin platform for unmanned combat systems was designed, and an online learning algorithm based on random finite set was proposed. The algorithm can use real-time collected sensor data to learn and predict the motion mode and trajectory of the UGV online. It is an important tool for sensing the battlefield environment. Similarly, it focuses on the combat scenario. The construction and simulation of complex models and decision support algorithms are not described. Therefore, the platform is not easy to extend to other stages such as Research & Development (R&D) stage, maintenance application, and training of unmanned equipment.

3 Cloud-Edge-End Collaborative Platform for Unmanned Ground Equipment Digital Twin

Considering the characteristics of the digital twin of UGE and the new challenges it faces, this paper designs a service-oriented cloud-edge-end collaborative digital twin platform architecture that tries to meet the various requirements of UGE. The architecture relies on the native cloud technology system[12, 13], takes the digital twin of battlefield environment and the digital twin of UGE as the starting point, deeply integrates the cloud resource aggregation ability, the edge side flexible deployment ability, and the end side fast response ability, and systematically analyzes. Then, we summarize various key technologies suitable for the development and design of the digital twin of UGE and the whole life cycle application, which need to be further broken through.

As shown in Fig. 1, the digital twin platform of UGE designed in this paper includes three levels: cloud, edge side, and end side from top to bottom. The cloud is divided into twin platform infrastructure layer, twin model development layer, and twin application service layer. The user of the cloud includes stakeholders, UGE design and manufacturing team, cloud service management and maintenance team, etc. The cloud is a powerful resource pool, and it is also a collaborative design, service encapsulation, and release platform for digital twin applications of UGE.

The edge side refers to the computing node deployed in the decentralized combat unit near the UGE. Its users should be the command center of each combat unit on the front line. The cloud and edge sides are deployed with container engines and corresponding orchestration tools to facilitate the rapid migration and deployment of digital twin applications encapsulated in a service-oriented form. The edge side can apply to call the mature applications in the cloud resource pool at any time, and quickly form a customized twin application scenario through rapid orchestration.

The end/terminal side mainly refers to the onboard control platform of the UGE. Through the perception and action execution components of the UGE on the control platform, the basic information collection and perception functions could be completed so as to guarantee that tasks could be performed according to the decision.

The edge side can complete the deployment of control and decision-making algorithms with high real-time requirements, while the cloud can support large-scale training and updating tasks of perception and decision-making algorithms. Through the effective collaboration of cloud-edge-end, the digital twin platform can satisfy various complex requirements during the whole lifecycle of UGE.

3.1 Cloud twin infrastructure layer

This layer is the resource support layer to realize the digital twin platform, which mainly includes various resources for platform storage, computing, communication, and security. The storage resources mainly include various types of databases. The equipment digital twin will generate a large amount of

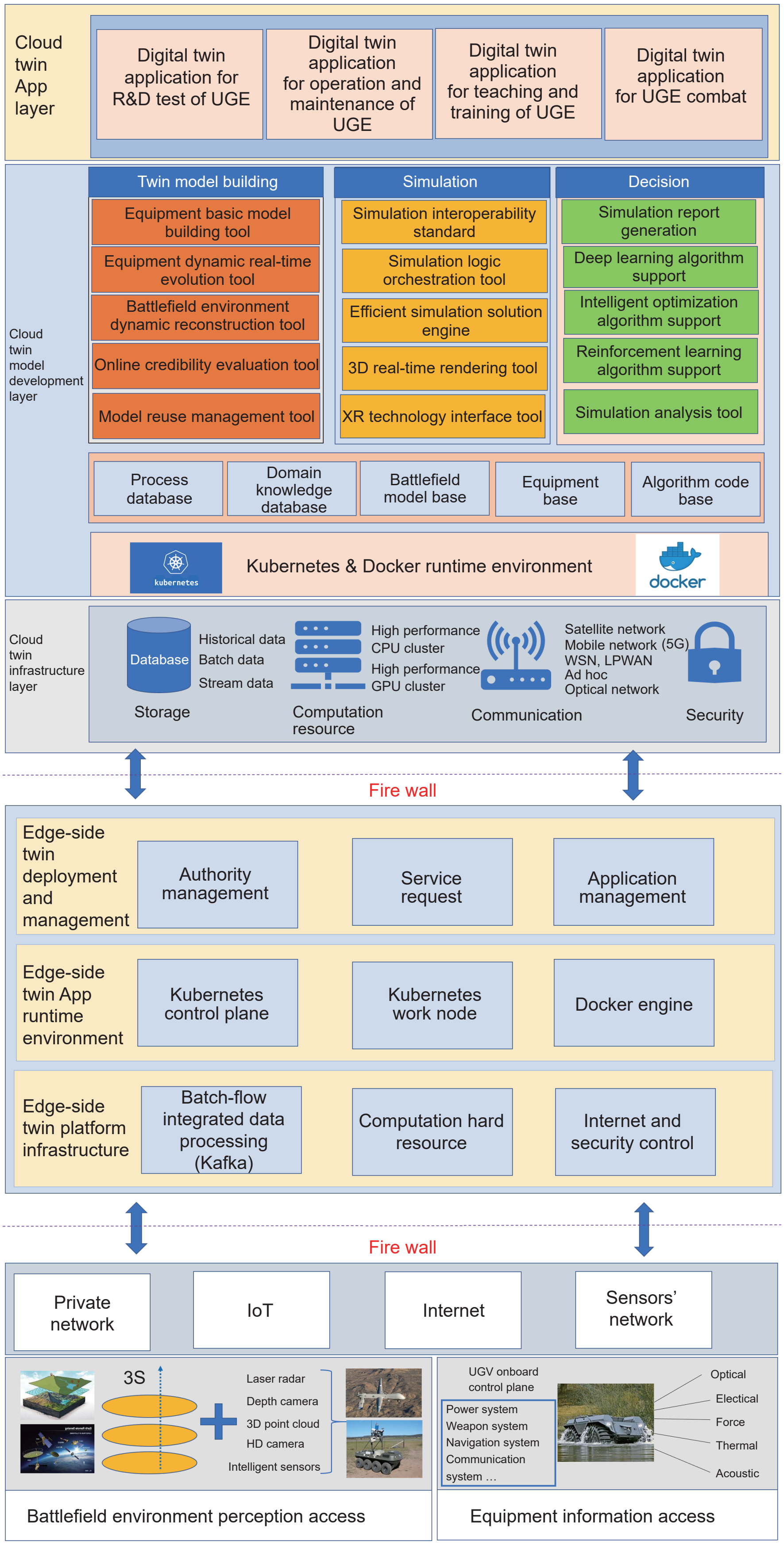

Fig. 1 Cloud-edge-end collaborative platform for unmanned ground equipment digital twin.

stream data in real time. The well-designed stream database can efficiently process various types of stream data (such as Kafka). It also includes various models, knowledge relational databases, and historical databases of various types of equipment. Computing resources include high-performance CPU and GPU clusters to meet the needs of real-time large-scale computing and environmental rendering of the digital twin platform. Communication resources are used to support low-latency and fast communication between twin platforms and physical equipment. It integrates satellite communication, Internet, 5G, WiFi, Wireless Sensor Networks (WSN), ad hoc, light network, and other communication methods that can be applied to different scenarios to adapt to the dynamic battlefield environment. The security resources are mainly to ensure the operation security, network security, confidentiality, and other requirements of the entire twin system, including various information encryption technologies, blockchain technology, backup technology, etc., to ensure the resilience and anti-attack ability of the platform operation.

3.2 Cloud twin model development layer

The twin model development layer is used to build various types of digital twins. It is the core of the entire digital twin cloud platform, providing a variety of environments, tools, and components needed to develop digital twin models. The twin model development layer deploys the container runtime environment and the Kubernetes (K8s) container orchestration environment, which is responsible for controlling the scheduling and deployment of resources required for container operation and network communication based on proxy mode. The development layer also includes development components such as development process database, equipment model database, battlefield environment database, domain knowledge database, and code library, which are used to support the reuse, reconstruction, and combination of models. The twin model development layer divides the development process of digital twin of UGE into three steps, which are twin model construction, simulation solution, and decision support. The respective key techniques will be discussed in the next part of this paper.

3.3 Cloud twin application layer

This layer is responsible for providing various typical applications developed and integrated by the twin model development layer and based on the service encapsulation of container technology, such as digital twin applications for UGE R&D and testing, digital twin applications for UGE capability verification, digital twin applications for UGE training and teaching, and digital twin applications for UGE operations.

Next, the structure and function modules of the edge side are introduced. Compared with the complex development environment and tool components of the cloud platform, the structure and function of the edge side are relatively simple. The main purpose of the edge side is to initiate a service request to the cloud according to the specific demand scenario, and quickly complete the deployment to meet the needs of digital twin real-time and personalized service for unmanned ground equipment.

The edge side also deploys a container orchestration and operating environment consistent with the cloud. From the bottom up, it includes the edge digital twin platform infrastructure layer, the edge twin application operating environment layer, and the edge twin application deployment and management layer. The infrastructure layer contains basic stream data processing databases for real-time interaction with unmanned ground equipment, basic computing hardware resources, and network and system security components. The application environment layer deploys container operating environments, such as Docker and container orchestration environment K8s.

By building a cloud-consistent operating environment, the deployment and migration capabilities of cloud applications are greatly facilitated, and the continuous delivery and maintenance of digital twin applications can be realized. It is convenient for the upgrade of digital twin model software and algorithms, which also makes edge-side applications have fault tolerance, disaster preparedness, and elastic scalability. It improves the adaptability of the UGE digital twin platform in complex and dynamic battlefield environment. The application deployment and management layer, mainly includes the rights management, service request, and application management functions, through this layer, the edge side can control the permission and version of application download and deployment request from the cloud, and manage the update and upgrade of applications and routine maintenance.

Finally, it is the end side, which refers to the structure and function module of the UGE vehicle onboard control platform. Its main task is to be responsible for the perception, acquisition, and transmission of real-time sensing data of physical entities and the reception, and transmission and execution of optimal control commands from the direction of digital twin platform. In the digital twin scenario of UGE, the sensing access layer mainly includes two tasks. On one hand, it is the perception of battlefield environment entities, and on the other hand, it is the perception of the state and performance of UGE.

4 Key Supporting Technology for the Platform

The construction of the digital twin platform for UGE described above requires the support of many key technologies. From the perspective of model engineering, it is necessary to consider the key technologies of the four stages, model building, model using, model evaluation, and model management, respectively. There has been many research progress in the above related technologies in the field, but they are still in the initial stage on the whole. There are still many tough problems that need to be broken through, and a complete technical system has not yet been formed. In the following, this paper will summarize the key technologies that support the realization of the functional modules of the designed digital twin platform for UGE, and point out the shortcomings of various key technologies and the future development direction.

Here, only the key technologies that are representative and need to be developed and improved to solve the various challenges faced by the digital twin of UGE described in this paper are selected. Sections 4.1−4.5 correspond to the twin building module of the proposed cloud twin model development layer in Fig. 1 and Sections 4.6 and 4.7 correspond to the simulation module and decision module of the cloud twin model development layer, respectively.

4.1 Digital twin basic model building technique for UGE

The digital twin basic model of UGE refers to the digital model that has not yet participated in the evolution on a certain time slice. In order to distinguish it from the dynamic evolution characteristics of digital twin, it is called the digital twin basic model. Establishing the digital twin basic model of UGE requires various advanced modeling and simulation technologies. The current field can be roughly divided into three technical categories, namely, mechanism-driven modeling technology, data-driven modeling technology, and mechanism and data hybrid-driven modeling technology, as described below.

(1) The mechanism model is also known as the mathematical model established by the “first principle”. Its construction depends on the mature mathematical theory of various disciplines, which is manifested as complex differential equations, partial differential equations, etc. It is the most widely used modeling and simulation method in multi-domain simulation software. However, many parameters in the model are difficult to obtain directly, and a large number of parameter identification experiments are needed. Moreover, the mathematical equation of the mechanism model is fixed, and its adaptive ability is limited. It cannot adapt to the simulation in complex uncertain environments, and the digital model constructed by it is difficult to perform real-time online evolution. The commonly used parameter identification methods in the field include unscented Kalman filter method, particle filter method, heuristic optimization algorithm, etc.[14, 15], but these methods cannot get rid of the tedious computational complexity.

(2) Data-driven modeling technology is an end-to-end black-box modeling technology that mines fixed patterns and associations from system input and output data. Common data-driven modeling methods include machine learning related methods (Support Vector Machine (SVM), decision tree, ensemble learning, etc.), deep learning related methods (Long Short-Term Memory (LSTM), Recurrent Neural Network (RNN), Gated Recurrent Unit (GRU), Temporal Convolution Network (TCN), Autoencoder, etc.), probabilistic statistical modeling methods (dynamic Bayesian network, Markov Chain Monte Carlo (MCMC), etc.), and traditional system identification methods (Neural Network Autoregressive with Exogenous Input (NNARX), Auto Regressive Moving Average (ARMA), etc.)[16−19]. In general, the dynamic data-driven model has poor interpretability, generalization, and robustness, and there are still bottlenecks in the application of industrial fields with high reliability requirements.

(3) The hybrid-driven modeling technology of mechanism and data fully integrates the interpretability of mechanism modeling and the powerful fitting and

representation ability of data-driven modeling. It studies how to integrate prior knowledge into the data-driven black box model, which makes the black box model more credible and enhances its generalization ability. It also greatly accelerates the convergence speed of the black box model and reduces the huge amount of data that its training relies on, for example, typical Physics Informed Neural Network (PINN), Physics Guided Neural Network (PGNN), Neural ODE (NODE)[20−23], and so on. However, this field is still in the stage of exploration and development, and there is no mature theoretical framework and application practice. How to integrate credible prior knowledge into data-driven models is still a problem that needs to be overcome.

4.2 Digital twin dynamic rapid reconstruction technology for battlefield environment

Constructing the digital twin of the battlefield environment is of great significance for the digital twin of the equipment to play a role. Dynamic rapid reconstruction of battlefield environment digital twin refers to the rapid modeling or reconstruction of dynamic battlefield environment model, including 3D geographic environment, personnel equipment, and other key elements, by using the existing model library and real-time updated environmental sensor data. For example, the mission planning of the UGE needs to refer to the twin model of the battlefield environment. At present, the construction of battlefield environment model is a concrete analysis of the specific situation. Usually, Remote Sensing, Global Position System, and Geographic Information System (3S) technology is used to explore and map the actual environment to obtain standard data, and then a model is formed through a lot of development work of professionals. The battlefield environment model constructed in this way is not only time-consuming and labor-intensive, but also difficult to reuse. When the real battlefield environment changes, it is inevitable to increase a lot of secondary development work. The real battlefield has the characteristics of diverse terrain, changeable weather, dynamic time, complex electromagnetic environment, and the uncertainty of human activities, which puts forward an urgent need for the digital twin dynamic reconstruction technology of battlefield environment.

Aiming at the digital twin dynamic reconstruction technology of battlefield environment, it is necessary to tackle key problems from two aspects. The first is to develop a meta-model construction method and basic model library for modern battlefield, which is convenient to inherit the meta-model template according to the specific needs of the battlefield, and quickly customize the development of real-time battlefield environment. The general battlefield includes three types of elements: our equipment and situation, enemy equipment and situation, and battlefield three-dimensional scene.

The second is to deeply study the intelligent 3D scene reconstruction technology based on deep learning. With the help of the trained intelligent vision algorithm, the collected 2D image information and the image depth information (point cloud, etc.) collected by 3D sensors (such as Light Detection and Ranging (LiDAR), Time of Flight sensor (ToF), etc.) can be used to quickly and automatically generate high-fidelity fine-grained 3D scene content. There are many good algorithms in the field, but there are still many problems to be overcome from the digital twin dynamic reconstruction of battlefield environment. It mainly includes 3D reconstruction technology of large-scale outdoor weak texture scene, high-precision 3D reconstruction of large scene with detail preservation, lightweight environment characterization technology adapted to battlefield game and communication limited environment, and multi-agent collaborative multi-node map verification and fusion technology. Breaking through the above key technologies plays an important role in promoting the implementation of digital twin dynamic reconstruction technology in battlefield environment.

4.3 Digital twin dynamic real time evolution technology for UGE

Dynamic evolution characteristics are an important feature of the digital twin model that is different from the traditional simulation model. How to use real-time sensor data to correct the twin model online and in real time to make it consistent with the internal mechanism of physical objects, such as performance degradation and model structure change, is the core issue that needs to be studied[24−26].

It is a very difficult task to establish an online digital twin model that can adapt to dynamic evolution, especially for the system model with high complexity. At present, the related theories and methods of incremental learning, lifelong learning, continuous learning or transfer learning in the field of deep learning, and the related theories of dynamic data-driven application system in the field of modeling and simulation can provide corresponding reference and guidance for evolution modeling.

Life-long learning and other related theories are aimed at continuously learning the implicit knowledge in new samples without forgetting the domain knowledge that the network has learned, so that the model continues to evolve and grow, and increasingly adapts to the sample and label distribution on the target domain[27]. The theory of dynamic data-driven application system is essentially an extension of Bayesian statistical theory. Its core technology lies in various filtering algorithms. Through the real-time acquisition of new data, the prior estimation is continuously corrected to obtain a more accurate probability distribution model, so as to predict the system behavior[28]. Similar theories include deep Markov model, Variational Autoencoders (VAE), etc. According to different digital twin needs, different evolution modeling methods can be selected to establish different types of models.

In terms of the implementation framework of digital twin dynamic real time evolution, it can be briefly divided into three steps. The first is data acquisition and preprocessing. According to modeling requirements and engineering practice, the observation variables are determined, many sensors are deployed scientifically, real-time operation data of equipment are obtained, and data are preprocessed such as singular value processing, time alignment, noise reduction filtering, etc., for subsequent use. The second is the determination of dynamic evolution triggering mechanism. Evolution triggering mechanism is a very important step for digital twin model to realize adaptive online evolution, which determines the instant of evolution. It can be further divided into three categories: periodic time triggering mechanism, non-periodic event triggering mechanism, and hybrid triggering mechanism. It is necessary to determine the evolution triggering mechanism according to the background and real-time requirements of the problem. The third is the design of the real-time evolution algorithm. If the self-evolution is triggered, digital twin model will evolve itself using real-time sensor data driven by the evolution algorithm, such as commonly used gradient descent in deep learning, variational inference in deep Markov models, heuristic optimization algorithms in parameter identification, and so on.

4.4 Rapid model combination and reuse technology for UGE digital twin

Rapid model combination and reuse is one of the key technologies for UGE digital twin construction. Its purpose is to semi-automatically or automatically reuse existing components from the combination model library according to specific task scenarios, reuse previous domain knowledge, and quickly complete the configuration of digital twin models[29]. This paper tries to break through the rapid combination and reuse technology of model, mainly from two aspects. One is the support of model running environment. Using the native cloud technology described above, the developed model is service-oriented encapsulated, and the unified container running engine is configured, which can easily migrate and deploy the application of digital twin model. In addition, the container orchestration technology can easily realize the integration of different applications, which is conducive to the integrated simulation of cross-domain cross-platform heterogeneous models.

The second is the description of digital twin meta-model. The meta-model is a higher-level formal description of the complex model structure. The internal logical relationship between complex model components is expressed. It can be said that the meta-model is a knowledge graph that realizes model combination and reuse (including reconstruction). At present, the SysML language is widely used in the field. SysML describes the system components, architecture, behavior, and correlation through multiple sets of views such as requirements, structure, and behavior. In particular, Beihang University proposed the design of Model-Based System Engineering (MBSE) oriented complex product modeling and simulation integrated language-X language[30], which can make up for the lack of SysML language that does not support simulation and lay the foundation for the localization of system-level modeling language. It is of great significance to promote the rapid combination and reuse of models for digital twins by deeply studying the meta-model design and syntax, semantics, pragmatics standards, and specifications of digital twins for UGE and battlefield environment.

4.5 Dynamic credibility evaluation technology of digital twin

Credible digital twin can play its application value. Untrustworthy digital twin can not only bring positive value but also bring devastating damage to equipment. However, in the current field, it is not comprehensive and scientific to consider the credibility evaluation only from the perspective of the fidelity of the twin model shape and the output of the twin model simulation data. The credibility of the digital twin should be analyzed and studied in a specific demand scenario from a unified perspective of the whole life cycle of the twin model development. The perfect theory and method of equipment digital twin credibility evaluation can not only evaluate the constructed digital twin afterwards, but also provide guidance for the construction process of digital twin.

The credibility evaluation of equipment digital twin system is different from the credibility in the field of traditional modeling and simulation. This difference mainly comes from the essential characteristics of digital twin, which is mainly reflected in the following aspects. Firstly, the object of credibility evaluation of equipment digital twin system is not only the digital twin model of equipment, but also the physical entity of equipment, which constitutes a symbiotic system. In addition, the equipment digital twin has the characteristics of dynamic real-time evolution, an important feature of digital twin different from traditional modeling and simulation. The credibility of the evolution mechanism itself will directly affect the credibility of the digital twin model. The dynamic evolution characteristics of the whole life cycle of the equipment digital twin require that its credibility evaluation should also be dynamic. Obviously, the digital twin is a time-varying digital model, and its credibility evaluation results have timeliness, finally, the equipment digital twin has multi-dimensional characteristics. Due to the complexity of the equipment itself, its digital twin must have multi-disciplinary, multi-physical, multi-granularity, and multi-scale characteristics. Its credibility evaluation should fully consider the internal correlation coupling mechanism of the equipment and conduct a comprehensive evaluation from a multi-dimensional perspective.

4.6 Efficient simulation solution technology for UGE digital twin

Different from traditional modeling and simulation, digital twin puts forward high requirements for the real-time performance of online simulation. In order to meet the requirements of real-time performance, it is necessary to make efforts in communication technologies, such as 5G, 6G, and other new generation communication technologies. It is also necessary to make efforts at the hardware level supporting distributed high-performance computing (such as high-performance GPU computing cluster). In addition, a very important key technology is the efficient simulation solution technology for digital twin. Digital simulation solution is essentially a process of computer numerical solution. In addition to the hardware performance of the computer itself, the efficiency of numerical solution is mainly determined by two major factors. One is the complexity of the simulation model itself, and the other is the calculation mode of numerical solution. To break through the efficient simulation solution technology for digital twin, we should mainly focus on the above two points. Here, we mainly describe the model reduction technology and numerical solution mode to reduce the complexity of the model.

Model reduction, simply speaking, is to simplify the model and reduce the amount of calculation under the premise of ensuring the setting accuracy. Common model reduction methods can be divided into four categories: time domain, frequency domain, time-frequency domain, and intelligent optimization theory. This paper focuses on the new generation of artificial intelligence technology in intelligent optimization methods. Using the powerful fitting and characterization capabilities of deep neural networks, it can fit many complex partial differential equations (such as common heat conduction equations, Navier-Stokes turbulence equations, etc.). The calculation method of neural network linearization can greatly save calculation time and efficiency. The hot PINN technology in the current field is a typical representative of this type of technology. The famous finite element simulation software provider Ansys claims to also use artificial neural networks to achieve model reduction, which can achieve digital twin-level real-time finite element simulation.

The new numerical solution mode also points out the way for the efficient simulation solution technology for digital twins. In recent years, thanks to the efficient parallel solution ability of GPU for matrix operation, deep learning technology has developed by leaps and bounds. Further discussion on how to apply GPU parallel computing capabilities to scientific computing fields such as differential equations or partial differential equations solving, and designing novel cloud-edge collaborative parallel and efficient computation framework will greatly benefit the development of digital twin technology. In addition, the CPU numerical solution mode currently dependent on the X86 architecture is transferred to the Field Programmable Gate Array (FPGA) chip, thereby improving the computational efficiency, which has also received extensive attention from the industry. However, due to the limitations of memory and computational theory, the current maturity is not high. The next generation of computers based on quantum physics also opens up the way for people to update the computational mode. The birth of quantum computers in the future may push the digital twin to another climax.

4.7 Cloud-edge-end collaborative online intelligent control and decision-making technology for UGE combat

The digital twin models of equipment, people, and environment in the battlefield are connected to the combat cloud platform, and the battlefield digital twin model can be further formed. Based on the battlefield digital twin model, the tasks of battlefield situation perception and strategic and tactical deduction can be further completed. In the future, due to the continuous improvement of the level of informatization, networking, and intelligence, the rhythm of the war will gradually accelerate. The battlefield form will change rapidly, and a large amount of data will be generated in the short term. The commander may need to respond quickly in a few seconds, which will bring a big challenge to the commander. The use of artificial intelligence means, based on the powerful computing and solving ability of the computer, can assist the commander to make decisions quickly, and find the optimal or sub-optimal combat plan. And the unmanned combat cluster can even be taken over by the cloud brain to perform specific tasks through distributed online control, such as cluster raids on designated targets and remote assistance fire strikes. This is so-called UGE online intelligent control and decision-making technique based on battlefield digital twin.

Based on the battlefield digital twin model, with the help of artificial intelligence technologies such as deep learning and reinforcement learning, the virtual-real symbiosis and closed-loop optimization of the entire battlefield digital twin system can be formed. The current field can provide guidance and reference for online intelligent control and decision-making optimization technology based on digital twin. It is mainly composed of the following types of technologies, machine vision-driven situation awareness technology, using feature extraction capabilities such as graph neural network and convolutional neural network to perceive the changes and characteristics of the enemy's combat mode, and make advanced predictions on its future operational capabilities and combat intentions. Deep reinforcement learning and heuristic multi-objective optimization algorithm-driven optimization techniques, aiming at the NP-hard problem of combinatorial optimization, use reinforcement learning algorithms or heuristic optimization algorithms to search for the optimal solution that satisfies the established constraints from the feasible solution space.

Using the battlefield digital twin model, it is expected to generate new tactical strategy creatively and break through the original cognitive limit. The distributed adaptive control technology of unmanned cluster realizes the model predictive control of unmanned equipment cluster based on digital twin, which helps unmanned cluster realize self-organizing and adaptive behavior ability for given tasks. Knowledge reasoning technology based on knowledge graph formalizes expert experience knowledge, constructs knowledge graph for target tasks, and finally forms knowledge reasoning engine to help commanders complete problem analysis and plan recommendation. Of course, the above technologies need to be further developed in terms of real-time performance, interpretability, universality, robustness, and credibility in order to truly empower the online intelligence and control technology of battlefield digital twins.

In summary, a reasonably designed cloud-edge-end collaborative digital twin platform architecture, and well developed above advanced support technology research, will effectively respond to the new challenges faced by UGE digital twin, such as complex environment, drastic changes, rapid decision-making, and others as described before.

However, the existing technologies still have limitations. In terms of digital twin basic model building, it has been found in practice that the digital twin dynamic system model of UGE developed in data-driven modeling manner such as neural networks still have problems including poor robustness and poor generalization capability. How to effectively integrate the discipline mechanism and prior knowledge into the data-driven model is still an urgent problem to be solved. In terms of real-time 3D reconstruction and situational awareness of battlefield environment task, the distributed accurate perception and effective fusion of multi-source and multi-modal data based on the coordination of UGE still have shortcomings, especially in the scenario of game confrontation, which is vulnerable to interference conditions such as incomplete information acquirement and limited communication resource.

In view of the challenges of frequent or even drastic changes with unmanned ground equipment, the existing model adaptive dynamic evolution technologies are only applicable to the situations where equipment is subjected to small-scale changes such as wear and working condition changes. Whereas, for large-scale behavior changes of unmanned ground equipment, we can only try to reconstruct the digital twin model. Under this circumstance, it is necessary to rely on the MBSE methodology and software tools with machine automatic reasoning and optimization capability.

In view of the dynamic credibility evaluation of digital twins, it is still difficult to design a digital twin evaluation system that can truly support dynamic online credibility evaluation. This difficulty stems from two aspects. One is the lack of recognition of the concept of credibility of digital twins. Another is the dynamic evolution characteristics of digital twin, which blurs the line between model construction stage and model using stage.

In terms of the simulation solution engine for digital twin, the development of a simulation engine that can simultaneously support the solution of AI algorithms such as deep neural networks, and efficient parallel solution of complex differential and partial differential equations/groups will provide guarantee for the operation of the entire digital twin system.

For the decision support of unmanned ground equipment based on digital twins, based on the credible digital twin model, we can make use of advanced artificial intelligence methods including deep reinforcement learning to carry out intelligent inference, optimization, and other activities in virtual space. However, how to design the interaction mechanism between decision optimization algorithm and unmanned ground equipment digital twin system, including interoperable interface, super real-time simulation time management, new and old algorithm update exchange mechanism, etc., still needs a complete theoretical and technical study.

5 Main Workflow of Proposed UGE Digital Twin Platform

Figure 2 shows the workflow of the digital twin platform architecture proposed in this paper, which is briefly analyzed below. Figure 2a shows the workflow of digital twin service requests, personalized service customization, and application deployment for UGE. Users determine the digital twin application to be deployed based on the specific requirements firstly. If the relevant digital twin application can be queried on the cloud platform, the user at the edge side can directly initiate a service request to the cloud platform and then realize rapid deployment of application. After deployment, the application is connected with the actual UGE through the sensor network, private network, etc., to build a complete digital twin application system, and further realize the dynamic evolution of the digital twin through cloud-edge collaborative computing. If users are unable to find relevant applications that can be directly deployed on the cloud platform, they can leverage existing model library components in the cloud to rapidly develop customized digital twin applications according to the development mode of microservices.

Figure 2b shows the implementation of building complex fundamental models of UGE through cloud native technology. Using the twin model development layer tool of the proposed framework, simulation models of specific scenarios and fields of UGE can be built respectively and encapsulated in containers. For example, if we try to build UGE digital twin for path planning, we can respectively build environment rapid reconstruction service application, UGE dynamics simulation application, UGE electrical power simulation application, UGE control decision application, etc. These applications are finally managed through Kubernetes container orchestration tool, including mutual communication, interoperability, time synchronization, and event advancement among containers. Finally, the personalized digital twin application of UGE can be built. After that, the customized UGE digital twin application is migrated from the cloud to the designated working node on the edge side, and is connected with the actual ground

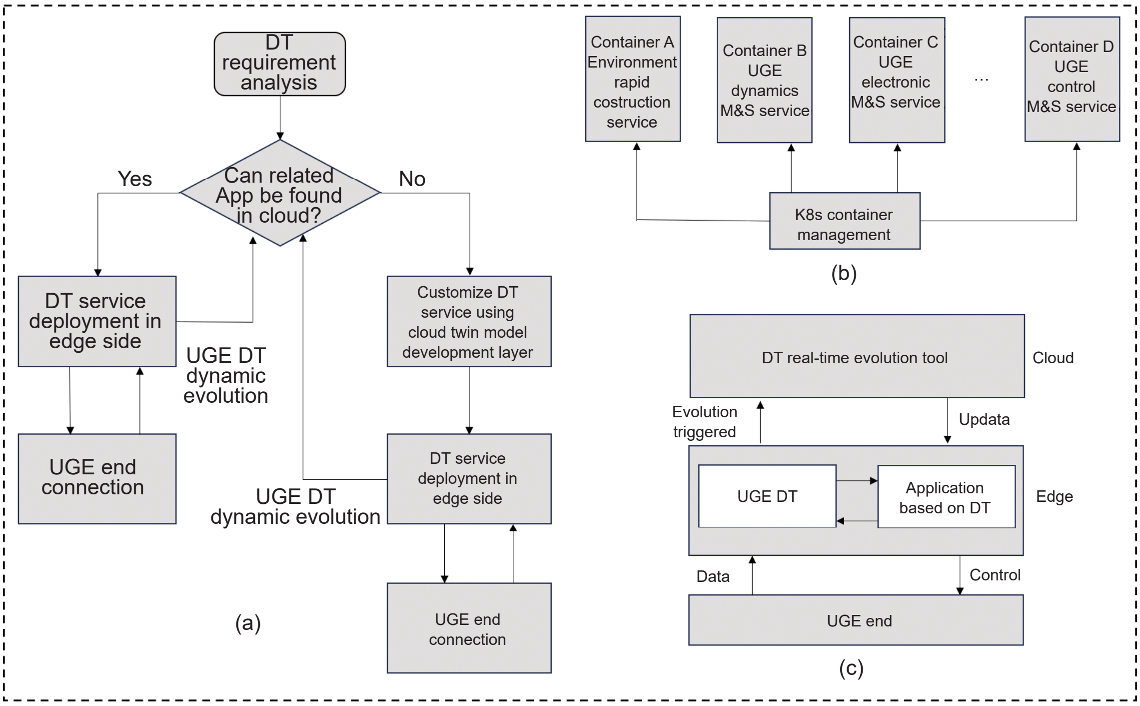

Fig. 2 Main workflow of cloud-edge-end collaborative UGE digital twin platform.

unmanned equipment to build a complete digital twin system.

Figure 2c describes the workflow of the dynamic evolution of UGE digital twins in Fig. 2a. Dynamic evolution is the core feature of digital twins, which is of great significance to credibly reflect the battlefield environment and the actual state of UGE in real time. In this paper, a cloud-edge collaborative approach is adopted to realize the dynamic evolution of digital twins. As shown in Fig. 2c, the digital twin application deployed at the edge side consists of two modules, digital twin model and twin-based application, which realize state perception and fast decision-making through real-time interaction with the physical entity. When the digital twin finds the abnormal deviation between itself and the physical entity, dynamic evolution operation is triggered. The powerful computing resources and real-time evolution tools on the cloud are invoked to update the digital twin and related applications, and the updated relevant parameters and components will be overloaded on the edge side.

Above all, the service-oriented cloud-edge-end collaborative UGE digital twin platform framework, key supporting technology, and related workflow designed in this paper based on the cloud native concept can well cope with the challenges of the UGE digital twin described above.

6 Conclusion

Unmanned ground equipment will play a huge role in future wars, and the development of digital twin related technologies will play an active role in the whole life cycle of research and development, operation and maintenance, and command and operation of unmanned ground equipment. This paper summarizes and analyzes the new challenges faced by the digital twin technology of UGE, and briefly analyzes the essence of digital twin technology. On this basis, a service-oriented cloud-edge-end collaborative digital twin platform architecture for UGE is designed and proposed. Finally, the key technologies of digital twin for UGE supporting the realization of platform functions are analyzed.

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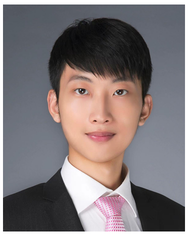

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