Parallel Training: An ACP-Based Training Framework for Iterative Learning in Uncertain Driving Spaces

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***Abstract*—The traffic environment and driving behaviors are of great complexity and uncertainty in our physical world. Therefore, training in the digital world with low cost and diverse complexities become popular for autonomous driving in recent years. However, the current training methods tend to be limited to static data sets and deterministic models that do not sufficiently take into account the uncertainty and diversity prevalent in real traffic scenarios. These approaches also limit more possibilities for the comprehensive development and optimization of vision systems. In this paper, we develop a parallel training method based on artificial systems, computational experiments, and parallel execution (ACP) for the intelligent optimization and learning of the aforementioned agents in uncertain driving spaces. Parallel training creates a virtual driving space following the instruction of the ACP approach and conducts large-scale rehearsal experiments for possible scenarios. By enhancing the diversity of virtual scenarios, intelligent vehicles are trained to respond and adapt to the diverse uncertainties in the physical real-world driving space. Specifically, parallel training first proposes a standard operating procedure for intelligent driving systems, namely the projection-emergence-convergence-operation (PECO) loop. Digital quadruplets for parallel training, i.e., physical, descriptive, predictive, and prescriptive coaches, are also proposed. With the guidance of parallel training, virtual and real-world driving spaces are set up in parallel and interact frequently. They are closely linked and unified in opposition to each other, ultimately building a parallel driving system that fulfills safety, security, sustainability, sensitivity, service, and smartness (6S).**

***Index Terms*—Parallel intelligence, parallel driving, digital quadruplets, parallel learning, digital twins, metaverses, automated driving, knowledge transfer.**

I. Introduction

DRIVING systems are typical complex and uncertain systems based on cyber-physical-social systems (CPSS) [1], [2]. At the holistic level, traffic participants are continually entering and leaving, while at the individual level, driving behavior, personalities, and moods are always shifting. What's more, driving systems are huge, with a high decision dimension, a large number of participants, and a vast volume of data. Last but not least, the driving system is uncertain, especially in light of potential behavior the drivers may have [3]. As a result, there are still numerous difficulties and obstacles associated with the intelligent management and control of complex systems, particularly driving systems.

Overall, the overarching objective of intelligent driving systems is to replace biological humans with intelligent agents in order to accomplish safety, security, sustainability, sensitivity, service, and smartness (6S) [4]. However, there are still several important issues with the practical implementation of smart driving technologies, including not robustness [5], [6], [7], [8], inefficiency [9], [10], [11], and high energy consumption [12], [13]. Intelligent vehicles that are not robust exhibit significant weaknesses when they encounter long-tail problems [14], [15]. In addition to failing to cut carbon emissions, inefficient intelligent vehicles exacerbate environmental harm and wasteful consumption. These are all important practical concerns that need to be addressed urgently in current intelligent driving systems.

In general, parallel intelligence [16], [17], [18], [19] can be applied to develop intelligence in complex systems and is more capable of solving the above-mentioned problems encountered in driving systems. Parallel intelligence investigates data-driven descriptive intelligence, experiment-driven predictive intelligence, and prescriptive intelligence with interactive

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feedback with a focus on CPSS, which are "human-in-the-loop" systems with high social and engineering complexity. Parallel intelligence provides agile, emergent, and convergent solutions for variable, diverse, and complex problems, which is based on artificial systems, computational experiments, and parallel execution(ACP) [20], [21], [22], [23]. The ACP method integrates information, psychology, simulation, and decision making in a computable, testable, and assessable fashion, offering fresh perspectives and approaches to study the control and management of complex systems, which is an important basic theory in the era of parallel intelligence. More than a dozen research areas, including parallel driving [24], [25], parallel traffic [26], [27], parallel control [28], [29], parallel vision [30], [31], [32], [33], and defense security [34], have benefited significantly from the ACP method.

ACP method and parallel intelligence are essential to achieving the primary goal of intelligent driving systems, which is to utilize well-trained agents rather than people in order to control and manage vehicles to meet users' needs. The term "meet users' needs" is to experiment and evaluate well-trained agents by setting task goals and certain test conditions in order to make the agents evolve and meet users' needs finally. Among all, a). What test tasks and conditions are appropriate? b). How and in which direction does the development evolve? c). When is it said to meet users' needs? The three key issues, W^2H of testing, must also be addressed during the investigation and assessment of intelligent driving systems. And the term "well-trained" refers to learning and training under the direction of data, expert knowledge, other agents, and even themselves, with the goal of helping the target agents develop fundamental driving skills. Likewise, a). What is specifically chosen as guidance? b). How should the guidance be delivered? and c). When&Where should coaching take place to ensure its efficacy? The three key issues, W^2H of training, must be addressed throughout the instruction and study of intelligent driving systems.

In response to the primary goal of intelligent driving systems, parallel driving [24], [35] is dedicated to solving the problem of how to replace human drivers with well-trained intelligent agents reliably and efficiently. Physical vehicles, descriptive virtual vehicles, predictive virtual vehicles, and prescriptive virtual vehicles were proposed as digital quadruplets [25] in parallel driving. These vehicles interact with one another to enable operation management, online condition monitoring, and emergency takeover for autonomous driving. At the same time, the three virtual vehicles act as the three "guardian angels" of the physical vehicle in various ways. The descriptive vehicle is responsible for building an accurate model of the real vehicle and the road environment, the predictive vehicle aims to make the correct arithmetic and analysis of the decision making and planning of the descriptive vehicle, and the prescriptive vehicle aims to guide the real vehicle to take the correct action in different driving scenarios. This makes genuine intelligent driving systems safer, more effective, and more dependable and helps to accomplish 6S eventually.

Parallel testing [36], [37] explores and expands the boundary capabilities of parallel driving systems to continuously meet users' demands, which is one of the elements in the primary goal of intelligent driving systems. Specifically, users' requirements may be continuously adjusted at small scales and slowly enhanced at large scales. For the W^2H issues involved in the experimentation and evaluation of complex intelligent driving systems, parallel testing suggests a virtual-real interactive vehicle intelligence evaluation and expansion strategy. The parallel test builds a human-in-the-loop intelligence test model by combining the benefits of both human experts and computer systems. This allows the driving system to have the cognitive mechanism to automatically upgrade itself under the guidance of human experts. It also introduces adversarial learning models to automatically generate new tasks, which can present complex and dynamic traffic scenarios and prompt the trained intelligent vehicles to further improve their abilities and meet users' needs.

The aforementioned parallel testing and parallel driving methods mainly tackle the problems of making intelligent driving systems suit users' needs and how to replace people with intelligent agents in such systems, respectively. However, the sophistication of the underlying intelligent technology in the intelligent driving system has a significant impact on the intelligence level of the system. Therefore, it is necessary and urgent to start with the training of intelligent agents and enhance the fundamental intelligence capabilities of the intelligent driving system in order to considerably raise the intelligence level of the driving system.

In this paper, we propose the projection-emergence-convergence-operation (PECO) ring of parallel driving as well as a new theoretical framework and practical method of parallel training, for the W^2H problems encountered in the learning and training process of parallel driving systems. PECO builds a circular bridge between digital quadruplets in parallel driving. Furthermore, digital quadruplets in parallel training based on the ACP method and parallel intelligence are developed along with PECO, so that intelligent systems can learn and master foundational intelligent technologies to achieve cognitive intelligence, cryto intelligence, social intelligence, parallel intelligence, federated intelligence and ecological intelligence (6I). Specifically, the digital quadruplets in parallel training include physical coaches, descriptive coaches, predictive coaches, and prescriptive coaches. The intelligence of the parallel driving system is improved by parallel training with the digital coach quadruplets. The main developments in parallel training are briefly outlined here.

- PECO of parallel driving is proposed to describe the recommended operational flow of intelligent driving systems. Also, it builds connections between parallel driving, parallel training, and parallel testing.
- Digital quadruplets in parallel training which include physical, descriptive, predictive, and prescriptive coaches are introduced to solve the W^2H problems of training.
- By designing the parallel training methods for intelligent driving systems, the virtual and real driving spaces are parallel overall and partially interactive. The two driving spaces develop separately but are not completely isolated. They interact at the level of virtual and real entities.

The rest of this essay is structured as follows. We summarize and introduce related work in the following section. And Section

III is about the PECO for parallel driving. Then, the framework of parallel training with digital quadruplets is shown in Section IV. In Section V, the specific method for parallel training is proposed. Finally, the conclusion and future work are presented in VI.

II. Related Work

In this section, the existing work related to parallel learning and parallel execution is first presented, and the essential concepts of these approaches are frequently employed in frameworks and procedures of parallel training. Next, we demonstrate digital twins (DT) and metaverses utilized in the projection and emergence processes, as well as parallel recommendation widely used in the emergence and convergence processes. Finally, the ultimate goal of parallel training can be accomplished by introducing scenarios engineering in the development of trustworthy AI techniques.

A. Parallel Learning & Parallel Execution

Parallel learning [38] also originates from the ACP method, and it is a new theoretical framework for machine learning. By successfully addressing data shortage, information exchange, and action selection that are not well solved by traditional machine learning theories, it has garnered more and more attention from researchers in a variety of domains. The parallel learning framework comprises three components known as descriptive learning, predictive learning, and prescriptive learning. At the same time, three unique and cutting-edge learning methodologies are featured in parallel learning. a). Big data pre-processing methods by software-defined artificial systems are included. b). Data learning, which comprises ensemble learning and predictive learning, is employed. c). Data-action-guided prescriptive learning based on Merton's law is used. Nowadays, parallel learning has been applied to a variety of machine learning and intelligence tasks [39], and the digital quadruplets in parallel training are also closely related to the three learning methods in parallel learning.

Parallel execution [40], [41] is presented as an important part of the ACP. In most of the previous work, it has always been introduced as one of the most important methods to achieve parallel intelligence [19]. The specific approach of parallel execution is different in different application scenarios and methodologies. But in general, parallel execution is the effective control and management of the operation of complex systems through the interaction between actual and artificial systems. In this paper, we apply the fundamental concepts and theories of parallel execution to the parallel operations of virtual and real systems as well as the interaction between virtual and real entries throughout the parallel training process.

B. Digital Twins & Metaverses

Both digital twins [42], [43], [44] and metaverses [45], [46], [47] are hot research topics recently. The mirror space model, then known as the digital twins, was initially taught by Professor Grieves [48] in a product lifecycle management seminar at the University of Michigan. It is the process of realistically mapping all components over the whole lifecycle utilizing physical data, virtual data, and data on how those components interact with one another. The concept of metaverses, on the other hand, originates from science fiction, and there has been no accepted precise definition yet. However, metaverses can be roughly viewed as a collection of virtual worlds and a progression of digital twins. It simultaneously integrates the virtual reality [49], communication technologies [50], web3.0 [51], artificial intelligence (AI) [52], [53], cloud computing [54], Big Data [55], blockchain [56], [57], [58] and other new technologies as a virtual-reality social form and Internet application. It is possible to think of the connection between the metaverses and the physical world as a fusion of virtuality and reality. In terms of space and time, metaverses are virtual in the spatial dimension, but real in the temporal dimension.

Nowadays, digital twins and metaverses have been widely studied and applied in several scenarios. Digital twins have more developed applications, particularly in the areas of product design [59], industrial production [60], logistics and distribution [61], and equipment maintenance & management [62], [63]. Although scientific study on the metaverses is still in its early stage, multiple studies [64], [65], [66], [67] have indicated that it can outperform the digital twins in a wide range of areas thanks to its stronger capabilities and more sophisticated technologies. In the paper, the projection of the real driving space to the virtual driving space, as well as the prediction and emergence of virtual driving, is inseparable from the technologies related to digital twins and metaverses.

C. Parallel Recommendation

Recommendation systems (RS) have been widely applied in e-commerce, personalized advertising, and other applications. Since intelligent recommendation demands for intelligent transportation systems are numerous, Jin et al. [68] suggested a parallel recommendation approach and used it to make an intelligent traffic signal recommendation. The system has been deployed for a longer period of time in a practical application in Hangzhou, China, and has achieved a good performance. Additionally, a parallel recommendation engine called PRECOM [69], [70] is suggested for traffic control operations to reduce clogged roads in urban regions. An artificial system model, a computational experimentation module, and a parallel execution module make up the system's three conceptual parts. A graph model-based candidate generator [71], a spatio-temporal ranker, and a contextual re-ranker are also developed as three fundamental algorithmic processes. In addition, parallel recommendation systems have proven to be effective in supporting current human-in-the-loop control schemes in the practice of traffic control, operations, and management.

In parallel training, the parallel recommendation approach for intelligent transportation systems is generalized and applied to the convergence process following the emergence of driving strategies and traffic scenarios in virtual driving space for intelligent vehicles.

D. Scenarios Engineering

Rapidly evolving artificial intelligence techniques produce highly accurate outcomes at the sacrifice of reliability and interpretability. However, this is prone to bring about negative outcomes, a decline in confidence, and even catastrophic hazards. In order to create more reliable and trustworthy AI, a theoretical framework for scenarios engineering [4], [72] is presented. It includes six key dimensions, including intelligence and indices (I&I), calibration and certification (C&C), and verification and validation (V&V) [73], and it also addresses the issues of trust and reliability in future research directions and practical applications.

Similar to most intelligent systems, the ultimate goal of parallel driving systems is to make them reliably and efficiently intelligent. Even, driving systems have a more stringent need for safety and trust than general intelligent systems [74]. Therefore, the ultimate goal of parallel driving needs to be scientifically set and accurately achieved through scenarios engineering in parallel training.

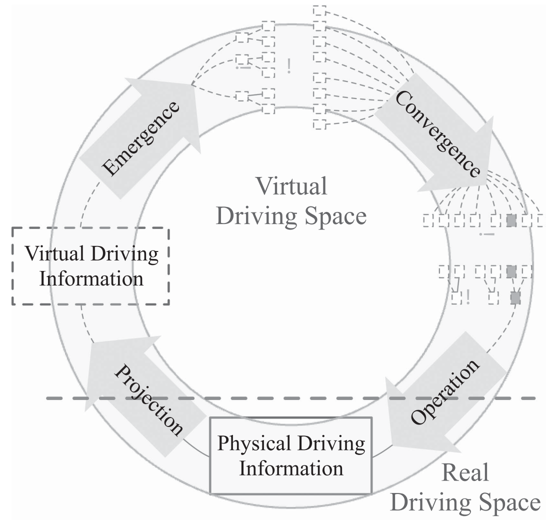

Fig. 1. The four stages of PECO: Projection, emergence, convergence, and operation.

III. PECO for Parallel Driving

The status of the vehicle, the surrounding environment, and other traffic participants are the three key elements that need to be considered and attended to at all times throughout a human driver's real driving process. Similarly, intelligent driving systems also need to consider all three in unison [75]. In parallel driving systems, the three key elements are projected into the virtual driving space by descriptive intelligence. Predictive intelligence is then used to forecast the surrounding environment, potential changes in other traffic participants, and potential aftereffects of this vehicle's future actions. Finally, prescriptive intelligence is used to the physical vehicle intelligently while transitioning into the following cycle. The PECO loop's fundamental procedure is presented above. And in what follows, the components of PECO and its relationship with the digital quadruplets in parallel driving are described in detail.

A. Components of PECO

As shown in the Fig. 1, PECO is built on both virtual and real driving spaces, and it creates a bridge between the two spaces. Specifically, the four components that make up PECO are projection, emergence, convergence, and operation. They create a flawless closed loop, which is a sophisticated procedure exclusive to parallel driving.

1) Projection: Numerous pieces of crucial driving information from the real driving space, such as driving behavior and the surrounding environment, are projected into the virtual driving space. The projection can be broadly classified into physical information projection and social information projection. Physical information primarily refers to the physical condition of the vehicles, the surrounding physical environment, etc., whereas social information primarily refers to the psychological state of the driver or even the passenger, the driving behavior of other traffic participants, etc. The acquisition of physical information in the real driving space can be accomplished easily through a variety of sensors such as cameras and radars. On the other hand, gathering social information is more challenging because it cannot be measured directly by traditional sensors. The general solution is to obtain social information indirectly by analyzing physical information over a period of time. The information-gathering process described above is the first stage of projection. Obviously, the next step is to project the gathered physical and social information from the real driving space to the virtual driving space with various advanced technologies such as game engines [21], [76], [77], [78], digital twins, and metaverses.

2) Emergence: Following the projection of driving information into the virtual driving space, the driving information that has already been obtained is first summarized and analyzed in detail. In the meantime, prospective scenarios are predicted in accordance with the stated task criteria during the emergence stage, and numerous options and outcomes' derivation are presented for each scenario. The prediction and simulation of possible prospective scenarios in virtual driving space based on the mapped driving information and the ongoing or possible tasks are the basis of emergence. Automatic design, generation, and rapid simulation of various possible scenarios can be achieved, based on technologies such as deep learning, reinforcement learning, and digital twins. The outcomes of these countermeasures can then be inferred and anticipated in the virtual driving environment based on the numerous prospective scenarios.

3) Convergence: Many potential outcomes and solutions will emerge in the virtual driving area during the emergence stage. The major issue to be resolved in the convergence stage is whether each potential scenario is actually plausible in the real driving spaces and which one or ones among all of the solutions are best suited for a particular circumstance. The assessment of each prospective scenario's plausibility and the necessity for resolution require expert knowledge from the real driving space. Even though the likelihood is remote, some potential

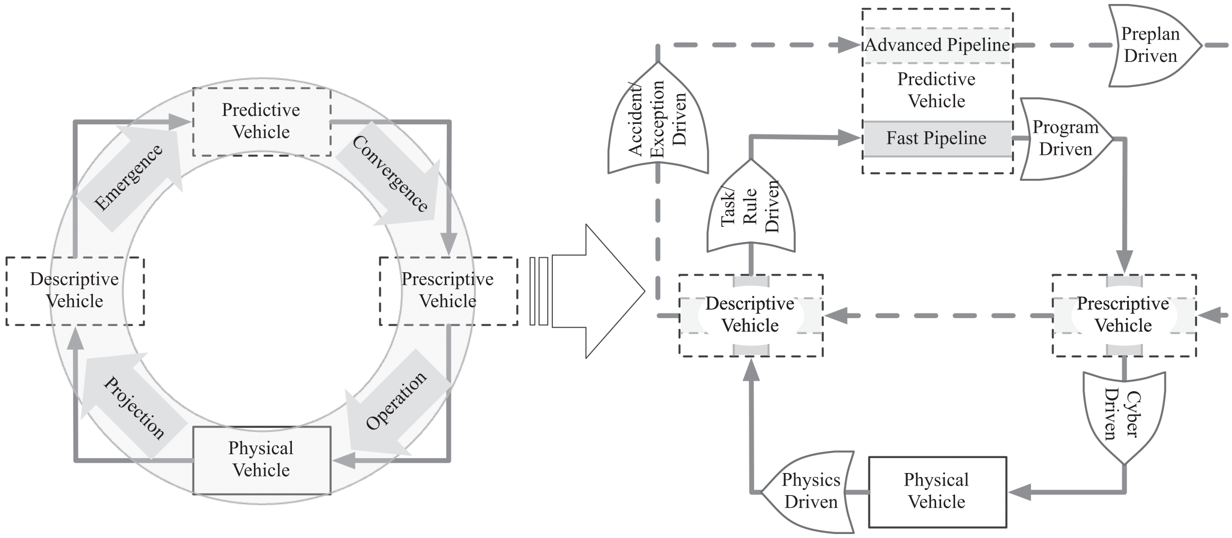

Fig. 2. Circular flow of digital quadruplets in parallel driving with the supervision of PECO.

outcomes merit careful consideration, while those that defy the rules of physics or go beyond our cognition can be easily discarded to prevent meaningless attrition. After screening the potential scenarios that need to be addressed, several solutions may be proposed for each scenario, which also need to be further screened for the optimal solution and then recommended for the real driving spaces. A crucial role is played by advanced recommendation models based on deep learning, knowledge graph, and reinforcement learning when combining scene information with inference results to suggest the best control strategy.

4) Operation: In contrast to the projection process, in the operation stage, the control policies recommended after emergence and convergence in the virtual driving space are synchronized to the real driving space for the ultimate implementation of intelligent driving. This is the last and most critical step in a PECO cycle, and it is strongly related to the final smooth operation of vehicles under the control of intelligent agents. Also, the accuracy of the execution determines the initial state of the next PECO cycle. Inaccurate executions of a large magnitude may not be reversible; however, inaccurate executions of a subtle magnitude can be effectively corrected after multiple PECO cycles.

B. PECO and Digital Quadruplets in Parallel Driving

PECO establishes smooth conversions among the digital quadruplets in parallel driving. Parallel driving, as illustrated in the Fig. 2, can improve the original "real-time occurrence, lagging solution" to "not yet occurring, advance planning" by diverging, computing, extrapolating, and preplanning in the virtual driving spaces.

First, the descriptive vehicles are initially formed by the physical vehicles in a physically driven manner during the projection process. Then, the predictive vehicle created in the emergence stages operates in two ways. For the pre-planned tasks and rules, solution programs are constructed through the fast pipeline, and for unforeseen accidents and exceptions, preplans are first formed through the advanced pipeline, and then specific programs are created by combining the information obtained from the projection in the physical world if they actually occur. Finally, the control strategies, which are acquired by the emergence and convergence in the virtual driving spaces, are then implemented in the physical vehicles by the prescriptive vehicles in a cyber-driven manner.

IV. Digital Quadruplets in Parallel Training

Similar to parallel driving, parallel training also involves digital quadruplets, namely descriptive coaches, predictive coaches, prescriptive coaches, and physical coaches. These coaches play crucial roles in the four phases of the PECO loop: projection, emergence, convergence, and operation, respectively. In the meantime, the PECO loop, as depicted in the Fig. 3, not only establishes the connection between parallel driving and parallel training but also permits the seamless integration of parallel testing into it. In simple terms, parallel testing is accountable for identifying the weaknesses in each PECO phase and determining whether the management and control of the physical vehicles have been successful in achieving anticipated goals following the operation phase. For the inappropriate description, the physical vehicles need to be re-projected to create the description vehicle. To get the most thorough coverage of the potential situations for the incomplete prediction, the predictive vehicles and the potential situations must be re-emerged. For scenarios that have been forecasted in the emergence phase but inaccurate prescriptions in the convergence phase, the prescriptive vehicles and recommended solutions need to be re-converged to produce more accurate suggestions and guidance. As mentioned previously, PECO is not only closely related to parallel testing but there is also a direct connection with parallel driving. Similarly, parallel training is also closely related to PECO and parallel driving, and its framework, i.e., digital quadruplets in parallel training and how they correspond to solving the W^2H problems of training, are described below in detail.

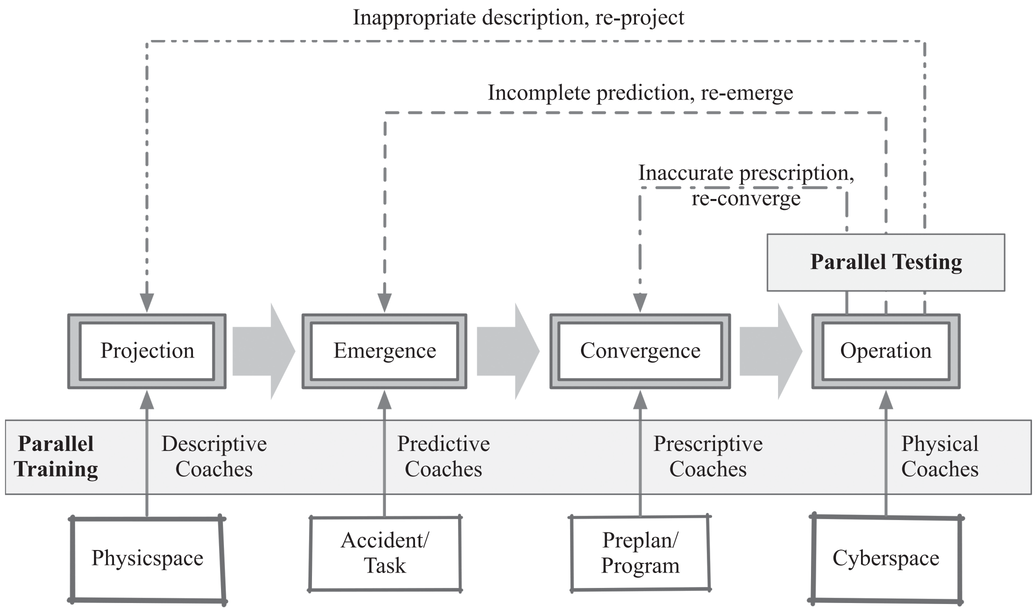

Fig. 3. Digital quadruplets in parallel training: Descriptive coaches, predictive coaches, prescriptive coaches, and physical coaches.

A. *Descriptive Coaches*

In the process of constructing the virtual driving spaces through the real driving spaces, descriptive vehicles are built in the virtual spaces by collecting data from the real spaces through various types of sensors and knowledge from human drivers through the knowledge graph. A major challenge for intelligent driving systems is to decide which guidance to employ within the vast amount of data and expertise. In this instance, the descriptive coaches participate in the training process as integrated instructors, addressing the issue of what is specifically chosen as guidance in the projection stage. The description coaches gather all types of information from physicspace to create a basic data and knowledge base. Then they clean up and analyze the vast amount of data and knowledge, weed out the unimportant information, and extract the important information. Eventually, the filtered information can be used as a more advanced version of data and knowledge base for the descriptive coaches to guide the projection process more efficiently.

B. *Predictive Coaches*

With the assistance and guidance of the predictive coaches, the predictive vehicles in the virtual driving spaces can make judgments in advance about the possible development direction of vehicles and the next situation to be encountered in the real driving space, while generating corresponding control strategies and extrapolating control results for the judgments. Predictive coaches address the issue of how the guidance should should be delivered in the emergence stage. Specifically, each potential scenario obtained during prediction does not exist independently but is closely related to the corresponding tasks or accidents. This is a vital assurance that guidance to the real driving spaces can be provided by the numerous potential scenarios formed during the emergence phase. Predictive coaches play significant roles in this process. As they are able to use the current target tasks or unforeseen accidents as the primary driving factor to comprehensively design potential scenarios that satisfy real needs under specific probability distribution criteria. Furthermore, they are able to identify whether they are faced with a task that they are already proficient at or an accident that they have not yet handled. They can then instruct the predictive vehicles to adopt various prediction and emergence strategies for different types of situations.

C. *Prescriptive Coaches*

One of the basic concepts of parallel intelligence is virtual guidance. The training procedure for each of the fundamental intelligent abilities of the vehicles is guided by prescriptive coaches, which provide planned, step-by-step, targeted advice at each stage. This can address the issue of effective coaching, i.e., when and where to coach to ensure effectiveness. Specifically, the multiple findings that are predicted and deduced throughout the emergence process must also be further converged and filtered before the optimal control policy is applied to the physical vehicles via prescriptive vehicles in accordance with the current scenarios and tasks. The convergence process entails the employment of sophisticated recommendation algorithms that combine current scenario data and task goals to prescribe the proper control policy at the proper time and location to ensure the effectiveness of intelligent vehicle control. The development of effective recommendation algorithms requires the assistance of a prescriptive coach which can combine data from real driving spaces with information about the target tasks or unforeseen accidents to produce the best recommendations. At the same time, the parallel coaches also instruct the vehicle to distinguish between task-specific programs and accident-specific preplans obtained in the virtual driving space. Programs that can be handled quickly are passed directly to the physical vehicle, while preplans that require further analysis and calculation are re-iterated in more loops of virtual driving spaces.

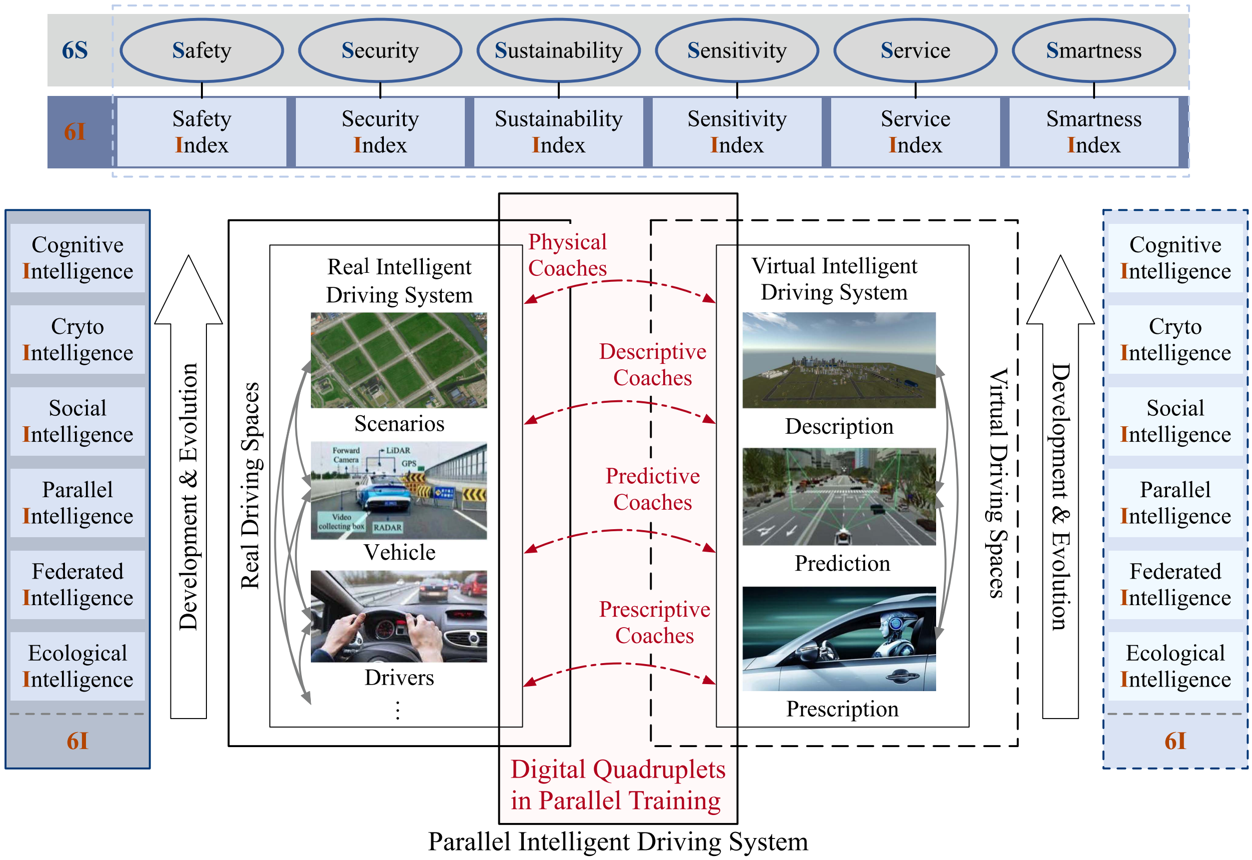

Fig. 4. Procedure of parallel training in parallel intelligent driving systems: Independence on a global scale and interaction on a local scale.

D. Physical Coaches

The effective control of physical vehicles by intelligent agents is the ultimate goal of parallel driving systems. Numerous sensors that are built into the physical vehicles are capable of gathering different types of data from real driving systems and serve as the foundation for building virtual driving systems. At the same time, the physical vehicles are also the primary recipients of various types of feedback and guidance from the virtual systems. During the operational phase, the best control strategies discovered through calculations in the virtual driving spaces are applied in the physical vehicles of real driving spaces. Although this process has undergone extensive testing and experimentation in virtual driving spaces, there are still certain risks associated with its direct application. The presence of physical coaches offers additional protection for safe driving while ensuring the implementation of the suggested driving strategies. The physical coaches first receive guidance information from cyberspace, while combining the current state of the physical vehicles and the surrounding environment to form an efficient limiter that meets the basic perception of the human drivers. In order to further lessen the safety issues brought on by the differences between the virtual driving spaces and the real driving spaces, the limiter is capable of imposing some straightforward, but very necessary limitations on the execution techniques to be applied by the physical vehicles.

V. PROCEDURE OF PARALLEL TRAINING

The generation of virtual entities in parallel driving systems and the dynamic interaction between virtual and real entities are the primary objectives of the parallel training procedure. Guided by the digital quadruplets of parallel training, three virtual entities of the parallel driving system, descriptive vehicles, predictive vehicles, and prescriptive vehicles are constructed with reference to the real entities of the intelligent driving system. Eventually, it is also with the aid of parallel training quadruplets, precise guidance to real entities can be accomplished. This is the specific procedure of parallel training in parallel driving.

As shown in the Fig. 4, the entities in the parallel driving systems mainly include scenarios, vehicles, drivers, other traffic participants, etc. And the virtual entities are description, prediction, and prescription. There are no more details to add to the above-detailed description of the specific roles played by each type of virtual entity. However, building virtual entities through real entities does not have a one-to-one correspondence and thus requires the deep involvement of parallel training quadruplets. Parallel training integrates the information collected from various real entities in the real driving spaces and passes it to the virtual entities in the virtual driving spaces separately, which is used to accurately construct the three types of virtual entities.

After the construction of the virtual and actual entities of parallel driving, the crucial significance of parallel training in the operation of intelligent systems can be summed up in terms of independence on a global scale and interaction on a local scale. Global-scale independence means that rather than completely modeling and reproducing the real driving systems, the virtual driving systems evolve independently and concurrently with it. This is excellent for broadening the range and likelihood of emergence in virtual driving spaces. In real driving spaces, the vehicles are controlled by human drivers or existing intelligence agents, producing some data, experience, and knowledge in the process. In the virtual driving spaces, the description, prediction, and prescription entities interact with one another continuously. Virtual intelligent driving systems are rapidly iterated and evolved through large-scale prediction experiments, inference evolution, and convergence verification, producing a vast amount of data, a wealth of experience, and trustworthy knowledge.

Local-scale interaction describes the frequent interaction between the entities in the virtual and real driving areas. On the one hand, to gain control over the actual driving system, various entities in the real system receive massive amounts of data and experience that are transferred to them selectively by the description, prediction, and prescription entities in the virtual systems. On the other hand, the virtual entities in the virtual driving spaces share the current state with the real entities in order to make the necessary corrections to prevent the violation of fundamental cognitive and physical laws.

Overall, by integrating digital quadruplets in parallel training into intelligent driving systems, virtual and real driving systems contribute to each other and develop & evolve simultaneously. Parallel training specifically aids in achieving the 6S of the intelligent driving systems by enhancing the six fundamental intelligence capacities of the driving systems, namely cognitive intelligence, cryto intelligence, social intelligence, parallel intelligence, federated intelligence, and ecological intelligence.

VI. Conclusion

The employment of parallel training methods to enhance fundamental intelligence capabilities of intelligent driving is a vital solution to the issue of how to train parallel driving systems effectively to considerably improve the intelligence of driving systems. We first describe the fundamental flow of parallel driving, known as the PECO loop briefly. Second, this study suggests a digital quadruplet framework for parallel training based on the ACP method that consists of physical coaches, descriptive coaches, predictive coaches, and prescriptive coaches. Meanwhile, the procedure of parallel training which emphasizes global-scale independence and local-scale interaction is also put forth.

The intelligent driving systems obtained through parallel training will definitely be greatly enhanced in terms of intelligence, efficiency, and safety. It is a good example that the training framework named Agent Manually via Evaluative Reinforcement (TAMER) [79] has been maturely applied in ChatGPT [80] and attracted wide attention. TAMER can take the knowledge of human markers and train agents in the form of rewarding feedback to speed up its convergence, which is also the focus emphasized in prescriptive coaches and closed-loop feedback of parallel training.

In the future, a variety of well-trained foundational intelligent technologies will be integrated together through the foundation models [81], [82] to create digital humans [83], [84] in intelligent vehicles. The digital humans can indirectly implement hardware-level activities by actually mobilizing the various domain controllers in the vehicle [85], while the human passenger simply needs to deliver general task commands without particular instructions. This will be the ultimate form of autonomous driving.

References

[1] F.-Y. Wang, "The emergence of intelligent enterprises: From CPS to CPSS," *IEEE Intell. Syst.*, vol. 25, no. 4, pp. 85–88, Jul./Aug. 2010.

[2] Y. Wang, J. Wang, Y. Cao, S. Li, and O. Kwan, "Integrated inspection on PCB manufacturing in Cyber–Physical–Social Systems," *IEEE Trans. Syst., Man, Cybern. Syst.*, early access, Dec. 20, 2022, doi: 10.1109/TSMC.2022.3229096.

[3] Q. Chen, Z. Wei, X. Wang, L. Li, and Y. Lv, "Social relation and physical lane aggregator: Integrating social and physical features for multimodal motion prediction," *J. Intell. Connected Veh.*, vol. 5, no. 3, pp. 302–308, 2022.

[4] X. Li, P. Ye, J. Li, Z. Liu, L. Cao, and F.-Y. Wang, "From features engineering to scenarios engineering for trustworthy AI: I&I, C&C, and V&V," *IEEE Intell. Syst.*, vol. 37, no. 4, pp. 18–26, Jul./Aug. 2022.

[5] J. Yin, D. Shen, X. Du, and L. Li, "Distributed stochastic model predictive control with Taguchi's robustness for vehicle platooning," *IEEE Trans. Intell. Transp. Syst.*, vol. 23, no. 9, pp. 15967–15979, Sep. 2022.

[6] K. Halder, U. Montanaro, S. Dixit, M. Dianati, A. Mouzakitis, and S. Fallah, "Distributed $H\infty$ controller design and robustness analysis for vehicle platooning under random packet drop," *IEEE Trans. Intell. Transp. Syst.*, vol. 23, no. 5, pp. 4373–4386, May 2022.

[7] Y. Sun, J. Li, X. Xu, and Y. Shi, "Adaptive multi-lane detection based on robust instance segmentation for intelligent vehicles," *IEEE Trans. Intell. Veh.*, vol. 8, no. 1, pp. 888–899, Jan. 2023.

[8] L. Li, M. Yang, H. Li, C. Wang, and B. Wang, "Robust localization for intelligent vehicles based on compressed road scene map in urban environments," *IEEE Trans. Intell. Veh.*, vol. 8, no. 1, pp. 250–262, Jan. 2023.

[9] N. Bhati, U. K. Kalla, B. Singh, and A. K. MIshra, "An intelligent control scheme for optimum efficiency and reduced emission operation of marine transportation system," *IEEE Trans. Intell. Transp. Syst.*, vol. 23, no. 10, pp. 17107–17118, Oct. 2022.

[10] L. Tan et al., "Speech emotion recognition enhanced traffic efficiency solution for autonomous vehicles in a 5G-enabled space–air–ground integrated intelligent transportation system," *IEEE Trans. Intell. Transp. Syst.*, vol. 23, no. 3, pp. 2830–2842, Mar. 2022.

[11] N. Goulet and B. Ayalew, "Distributed maneuver planning with connected and automated vehicles for boosting traffic efficiency," *IEEE Trans. Intell. Transp. Syst.*, vol. 23, no. 8, pp. 10887–10901, Aug. 2022.

[12] A. M. Bozorgi, M. Farasat, and A. Mahmoud, "A time and energy efficient routing algorithm for electric vehicles based on historical driving data," *IEEE Trans. Intell. Veh.*, vol. 2, no. 4, pp. 308–320, Dec. 2017.

[13] G. Feng, Y. Han, S. E. Li, S. Xu, and D. Dang, "Accurate pseudospectral optimization of nonlinear model predictive control for high-performance motion planning," *IEEE Trans. Intell. Veh.*, early access, Feb. 23, 2022, doi: 10.1109/TIV.2022.3153633.

[14] J. Wang, X. Wang, T. Shen, Y. Wang, Y. Tian, and F.-Y. Wang, "A long-tail regularization method for traffic sign recognition based on parallel vision," *IEEE J. Radio Freq. Identification*, vol. 6, pp. 957–961, 2022.

[15] Z. Liu, Z. Miao, X. Zhan, J. Wang, B. Gong, and S. X. Yu, "Large-scale long-tailed recognition in an open world," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, 2019, pp. 2537–2546.

[16] F.-Y. Wang, J. J. Zhang, and X. Wang, "Parallel intelligence: Toward lifelong and eternal developmental ai and learning in cyber-physical-social spaces," *Front. Comput. Sci.*, vol. 12, no. 3, pp. 401–405, 2018.

[17] F.-Y. Wang, "Parallel intelligence in metaverses: Welcome to Hanoi!," *IEEE Intell. Syst.*, vol. 37, no. 1, pp. 16–20, Jan./Feb. 2022.

[18] Y. Lin-Yao, C. Si-Yuan, W. Xiao, Z. Jun, and W. Chenghong, "Digital twins and parallel systems: State of the art, comparisons and prospect," *Acta Automatica Sinica*, vol. 45, no. 11, pp. 2001–2031, 2019.

[19] K. Liu, L. Li, Y. Lv, D. Cao, Z. Liu, and L. Chen, "Parallel intelligence for smart mobility in cyberphysical social system-defined metaverses: A report on the international parallel driving alliance," *IEEE Intell. Transp. Syst. Mag.*, vol. 14, no. 6, pp. 18–25, Nov./Dec. 2022.

[20] F.-Y. Wang, "Computational experiments for behavior analysis and decision evaluation of complex systems," *Acta Simulata Systematica Sinica*, vol. 5, pp. 893–897, 2004.

[21] X. Li, Y. Wang, K. Wang, L. Yan, and F.-Y. Wang, "The paralleleye-cs dataset: Constructing artificial scenes for evaluating the visual intelligence of intelligent vehicles," in *Proc. IEEE Intell. Veh. Symp.*, 2018, pp. 37–42.

[22] Y. Tian, X. Li, K. Wang, and F.-Y. Wang, "Training and testing object detectors with virtual images," *IEEE/CAA J. Automatica Sinica*, vol. 5, no. 2, pp. 539–546, Mar. 2018.

[23] W. Zhang, K. Wang, Y. Wang, L. Yan, and F.-Y. Wang, "A loss-balanced multi-task model for simultaneous detection and segmentation," *Neurocomputing*, vol. 428, pp. 65–78, 2021.

[24] F.-Y. Wang, N.-N. Zheng, D. Cao, C. M. Martinez, L. Li, and T. Liu, "Parallel driving in CPSS: A unified approach for transport automation and vehicle intelligence," *IEEE/CAA J. Automatica Sinica*, vol. 4, no. 4, pp. 577–587, 2017.

[25] T. Liu, X. Wang, Y. Xing, Y. Gao, B. Tian, and L. Chen, "Research on digital quadruplets in cyber-physical-social space-based parallel driving," *Chin. J. Intell. Sci. Technol.*, vol. 1, no. 1, pp. 40–51. 2019.

[26] C. Zhao, Y. Lv, J. Jin, Y. Tian, J. Wang, and F.-Y. Wang, "DeCAST in transverse for parallel intelligent transportation systems and smart cities: Three decades and beyond," *IEEE Intell. Transp. Syst. Mag.*, vol. 14, no. 6, pp. 6–17,Nov./Dec. 2022.

[27] X. Wang, T. Yao, S. Han, D. Cao, and F.-Y. Wang, "Parallel internet of vehicles:the acp-based networked management and control for intelligent vehicles," *Acta Automatica Sinica*, vol. 44, no. 8, pp. 1391–1404, 2018.

[28] F.-Y. Wang, "The DAO to metacontrol for metasystems in metaverses: The system of parallel control systems for knowledge automation and control intelligence in CPSS," *IEEE/CAA J. Automatica Sinica*, vol. 9, no. 11, pp. 1899–1908, Nov. 2022.

[29] Q. Wei, L. Wang, J. Lu, and F.-Y. Wang, "Discrete-time self-learning parallel control," *IEEE Trans. Syst., Man, Cybern. Syst.*, vol. 52, no. 1, pp. 192–204, Jan. 2022.

[30] J. Wang et al., "Parallel vision for long-tail regularization: Initial results from IVFC autonomous driving testing," *IEEE Trans. Intell. Veh.*, vol. 7, no. 2, pp. 286–299, Jun. 2022.

[31] J. Wang et al., "A parallel teacher for synthetic-to-real domain adaptation of traffic object detection," *IEEE Trans. Intell. Veh.*, vol. 7, no. 3, pp. 441–455, Sep. 2022.

[32] J. Wang, Y. Wang, Y. Tian, X. Wang, and F.-Y. Wang, "SST-GAN: Single sample-based realistic traffic image generation for parallel vision," in *Proc. IEEE 25th Int. Conf. Intell. Transp. Syst.*, 2022, pp. 1485–1490.

[33] W. Zhang, J. Wang, Y. Wang, and F.-Y. Wang, "ParaUDA: Invariant feature learning with auxiliary synthetic samples for unsupervised domain adaptation," *IEEE Trans. Intell. Transp. Syst.*, vol. 23, no. 11, pp. 20217–20229, Nov. 2022.

[34] J. Han et al., "Paradefender: A scenario-driven parallel system for defending metaverses," *IEEE Trans. Syst., Man, Cybern. Syst.*, early access, Dec. 22, 2022, doi: 10.1109/TSMC.2022.3228928.

[35] L. Chen, Y. Zhang, B. Tian, Y. Ai, D. Cao, and F.-Y. Wang, "Parallel driving OS: A ubiquitous operating system for autonomous driving in CPSS," *IEEE Trans. Intell. Veh.*, vol. 7, no. 4, pp. 886–895, Dec. 2022.

[36] L. Li et al., "Parallel testing of vehicle intelligence via virtual-real interaction," *Sci. Robot.*, vol. 4, no. 28, 2019, Art. no.eaaw 4106.

[37] L. Li, N. Zheng, and F.-Y. Wang, "A theoretical foundation of intelligence testing and its application for intelligent vehicles," *IEEE Trans. Intell. Transp. Syst.*, vol. 22, no. 10, pp. 6297–6306, Oct. 2021.

[38] Q. Miao, Y. Lv, M. Huang, X. Wang, and F.-Y. Wang, "Parallel learning: Overview and perspective for computational learning across syn2real and sim2real," *IEEE/CAA J. Automatica Sinica*, vol. 10, no. 3, pp. 594–622, 2023.

[39] X. Li, P. Ye, J. Jin, F. Zhu, and F.-Y. Wang, "Data augmented deep behavioral cloning for urban traffic control operations under a parallel learning framework," *IEEE Trans. Intell. Transp. Syst.*, vol. 23, no. 6, pp. 5128–5137, Jun. 2022.

[40] F.-Y. Wang, "Toward a paradigm shift in social computing: The ACP approach," *IEEE Intell. Syst.*, vol. 22, no. 5, pp. 65–67, Sep./Oct. 2007.

[41] Y. Ren, H. Jiang, X. Feng, Y. Zhao, R. Liu, and H. Yu, "ACP-based modeling of the parallel vehicular crowd sensing system: Framework, components and an application example," *IEEE Trans. Intell. Veh.*, early access, Nov. 14, 2022, doi: 10.1109/TIV.2022.3221927.

[42] S. Mihai et al., "Digital twins: A survey on enabling technologies, challenges, trends and future prospects," *IEEE Commun. Surv. Tut.*, vol. 24, no. 4, pp. 2255–2291, Fourthquarter 2022.

[43] Q. Wang, W. Jiao, P. Wang, and Y. Zhang, "Digital twin for human-robot interactive welding and welder behavior analysis," *IEEE/CAA J. Automatica Sinica*, vol. 8, no. 2, pp. 334–343, Feb. 2021.

[44] Z. Hu, S. Lou, Y. Xing, X. Wang, D. Cao, and C. Lv, "Review and perspectives on driver digital twin and its enabling technologies for intelligent vehicles," *IEEE Trans. Intell. Veh.*, vol. 7, no. 3, pp. 417–440, Sep. 2022.

[45] Y. Wang, Y. Tian, J. Wang, Y. Cao, S. Li, and B. Tian, "Integrated inspection of QoM, QoP, and QoS for AOI industries in metaverses," *IEEE/CAA J. Automatica Sinica*, vol. 9, no. 12, pp. 2071–2078, Dec. 2022.

[46] F.-Y. Wang, "Metavehicles in the metaverse: Moving to a new phase for intelligent vehicles and smart mobility," *IEEE Trans. Intell. Veh.*, vol. 7, no. 1, pp. 1–5, Mar. 2022.

[47] H. Zhang, G. Luo, Y. Li, and F.-Y. Wang, "Parallel vision for intelligent transportation systems in metaverse: Challenges, solutions, and potential applications," *IEEE Trans. Syst., Man, Cybern. Syst.*, early access, Dec. 20, 2022, doi: 10.1109/TSMC.2022.3228314.

[48] M. W. Grieves, "Product lifecycle management: The new paradigm for enterprises," *Int. J. Product Develop.*, vol. 2, no. 12, pp. 71–84, 2005.

[49] M. Lee and J. Ko, "Research on application of virtual reality technology to create metaverse podcasts," in *Proc. IEEE Int. Conf. Consum. Electron. - Taiwan*, 2022, pp. 133–134.

[50] J. N. Njoku, C. Ifeanyi Nwakanma, and D.-S. Kim, "The role of 5G wireless communication system in the metaverse," in *Proc. IEEE 27th Asia Pacific Conf. Commun.*, 2022, pp. 290–294.

[51] C. Chen et al., "When digital economy meets web3.0: Applications and challenges," *IEEE Open J. Comput. Soc.*, vol. 3, pp. 233–245, 2022.

[52] S. Badruddoja, R. Dantu, Y. He, M. Thompson, A. Salau, and K. Upadhyay, "Trusted AI with blockchain to empower metaverse," in *Proc. IEEE 4th Int. Conf. Blockchain Comput. Appl.*, 2022, pp. 237–244.

[53] O. Bouachir, M. Aloqaily, F. Karray, and A. Elsaddik, "AI-based blockchain for the metaverse: Approaches and challenges," in *Proc. IEEE Fourth Int. Conf. Blockchain Comput. Appl.*, 2022, pp. 231–236.

[54] J. Shen, T. Zhou, D. He, Y. Zhang, X. Sun, and Y. Xiang, "Block design-based key agreement for group data sharing in cloud computing," *IEEE Trans. Dependable Secure Comput.*, vol. 16, no. 6, pp. 996–1010, Nov./Dec. 2019.

[55] M. Zhou, "Editorial: Evolution from AI, IoT and Big Data Analytics to Metaverse," *IEEE/CAA J. Automatica Sinica*, vol. 9, no. 12, pp. 2041–2042, Dec. 2022.

[56] K. Gai, S. Wang, H. Zhao, Y. She, Z. Zhang, and L. Zhu, "Blockchain-based multisignature lock for UAC in metaverse," *IEEE Trans. Computat. Social Syst.*, early access, Dec. 13, 2022, doi: 10.1109/TCSS.2022.3226717.

[57] S. K. Dwivedi, R. Amin, and S. Vollala, "Blockchain-based secured IPFS-enable event storage technique with authentication protocol in VANET," *IEEE/CAA J. Automatica Sinica*, vol. 8, no. 12, pp. 1913–1922, Dec. 2021.

[58] Mamta, B. B. Gupta, K. -C. Li, V. C. M. Leung, K. E. Psannis, and S. Yamaguchi, "Blockchain-assisted secure fine-grained searchable encryption for a cloud-based healthcare cyber-physical system," *IEEE/CAA J. Automatica Sinica*, vol. 8, no. 12, pp. 1877–1890, Dec. 2021.

[59] C. Wang and Y. Li, "Digital-twin-aided product design framework for IoT platforms," *IEEE Internet Things J.*, vol. 9, no. 12, pp. 9290–9300, Jun. 2022.

[60] F. Tao, H. Zhang, A. Liu, and A. Y. C. Nee, "Digital twin in industry: State-of-the-art," *IEEE Trans. Ind. Inform.*, vol. 15, no. 4, pp. 2405–2415, Apr. 2019.

[61] M. Stan, T. Borangiu, and S. Răileanu, "Data- and model-driven digital twins for design and logistics control of product distribution," in *Proc. IEEE 23 rd Int. Conf. Control Syst. Comput. Sci.*, 2021, pp. 33–40.

[62] R. Chen, C. Jin, Y. Zhang, J. Dai, and X. Lv, "Digital twin for equipment management of intelligent railway station," in *Proc. IEEE 1st Int. Conf. Digit. Twins Parallel Intell.*, 2021, pp. 374–377.

[63] H. Liao et al., "Cloud-edge-device collaborative reliable and communication-efficient digital twin for low-carbon electrical equipment management," *IEEE Trans. Ind. Inform.*, vol. 19, no. 2, pp. 1715–1724, Feb. 2023.

[64] Y. Liu et al., "Radarverses in metaverses: A CPSI-based architecture for 6S radar systems in CPSS," *IEEE Trans. Syst., Man, Cybern. Syst.*, early access, Dec. 22, 2022, doi: 10.1109/TSMC.2022.3228590.

[65] W. Zheng, L. Yan, W. Zhang, L. Ouyang, and D. Wen, "D $\rightarrow$ k $\rightarrow$ I: Data-knowledge-driven group intelligence framework for smart service in education Metaverse," *IEEE Trans. Syst., Man, Cybern. Syst.*, early access,Dec. 20, 2022, doi: 10.1109/TSMC.2022.3228849.

[66] J. Yang, X. Wang, and Y. Zhao, "Parallel manufacturing for industrial Metaverses: A new paradigm in smart manufacturing," *IEEE/CAA J. Automatica Sinica*, vol. 9, no. 12, pp. 2063–2070, Dec. 2022.
[67] X. Wang, M. Kang, H. Sun, P. de Reffye, and F.-Y. Wang, "DeCASA in agriVerse: Parallel agriculture for smart villages in Metaverses," *IEEE/CAA J. Automatica Sinica*, vol. 9, no. 12, pp. 2055–2062, Dec. 2022.
[68] J. Jin, H. Guo, J. Xu, X. Wang, and F.-Y. Wang, "An end-to-end recommendation system for urban traffic controls and management under a parallel learning framework," *IEEE Trans. Intell. Transp. Syst.*, vol. 22, no. 3, pp. 1616–1626, Mar. 2021.
[69] J. Jin et al., "PRECOM: A parallel recommendation engine for control, operations, and management on congested urban traffic networks," *IEEE Trans. Intell. Transp. Syst.*, vol. 23, no. 7, pp. 7332–7342, Jul. 2022.
[70] J. Jin et al., "An agent-based traffic recommendation system: Revisiting and revising urban traffic management strategies," *IEEE Trans. Syst., Man, Cybern. Syst.*, vol. 52, no. 11, pp. 7289–7301, Nov. 2022.
[71] D. Cai, S. Qian, Q. Fang, J. Hu, W. Ding, and C. Xu, "Heterogeneous graph contrastive learning network for personalized micro-video recommendation," *IEEE Trans. Multimedia*, early access, Feb. 14, 2022, doi: 10.1109/TMM.2022.3151026.
[72] J. Lu, X. Wang, X. Cheng, J. Yang, O. Kwan, and X. Wang, "Parallel factories for smart industrial operations: From big ai models to field foundational models and scenarios engineering," *IEEE/CAA J. Automatica Sinica*, vol. 9, no. 12, pp. 2079–2086, Dec. 2022.
[73] F.-Y. Wang et al., "Verification and validation of intelligent vehicles: Objectives and efforts from China," *IEEE Trans. Intell. Veh.*, vol. 7, no. 2, pp. 164–169, Jun. 2022.
[74] X. Wang et al., "Safety-balanced driving-style aware trajectory planning in intersection scenarios with uncertain environment," *IEEE Trans. Intell. Veh.*, early access, Jan. 26, 2023, doi: 10.1109/TIV.2023.3239903.
[75] D. Cao et al., "Future directions of intelligent vehicles: Potentials, possibilities, and perspectives," *IEEE Trans. Intell. Veh.*, vol. 7, no. 1, pp. 7–10, Mar. 2022.
[76] X. Li, K. Wang, Y. Tian, L. Yan, F. Deng, and F.-Y. Wang, "The ParallelEye Dataset: A large collection of virtual images for traffic vision research," *IEEE Trans. Intell. Transp. Syst.*, vol. 20, no. 6, pp. 2072–2084, Jun. 2019.
[77] A. Dosovitskiy, G. Ros, F. Codevilla, A. Lopez, and V. Koltun, "CARLA:, "An open urban driving simulator," in *Proc. Conf. robot Learn.*, 2017, pp. 1–16.
[78] J. K. Haas, "A history of the unity game engine," *Diss. Worcester Polytech. Inst.*, 2014.
[79] W. Bradley Knox and P. Stone, "TAMER: Training an agent manually via evaluative reinforcement," in *Proc. IEEE 7th Int. Conf. Develop. Learn.*, 2008, pp. 292–297.
[80] F.-Y. Wang, Q. Miao, X. Li, X. Wang, and Y. Lin, "What does ChatGPT say: The Dao from algorithmic intelligence to linguistic intelligence," *IEEE/CAA J. Automatica Sinica*, vol. 10, no. 3, pp. 575–579, 2023.
[81] J. Wang et al., "A framework and operational procedures for metaverses-based industrial foundation models," *IEEE Trans. Syst., Man, Cybern. Syst.*, early access, Dec. 16, 2022, doi: 10.1109/TSMC.2022.3226755.
[82] Y. Tian, J. Wang, Y. Wang, C. Zhao, F. Yao, and X. Wang, "Federated vehicular transformers and their federations: Privacy-preserving computing and cooperation for autonomous driving," *IEEE Trans. Intell. Veh.*, vol. 7, no. 3, pp. 456–465, Sep. 2022.
[83] J. Wang, Y. Tian, and Y. Wang et al., "Digital workers in industrial Metaverses: From robotic process automation to digital process intelligence," *J. Intell. Sci. Technol.*, vol. 2, no. 2, pp. 7–11, 2022.
[84] Y. Wang, J. Wang, Y. Tian, X. Wang, and F.-Y. Wang, "Digital workers in Cyber–Physical–Social systems for PCB manufacturing," *IEEE J. Radio Freq. Identification*, vol. 6, pp. 688–692, 2022.
[85] D. Wang and S. Ganesan, "Automotive domain controller," in *Proc. IEEE Int. Conf. Comput. Inf. Technol.*, 2020, pp. 1–5.

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