Perspective

Parallel Sensing in Metaverses: Virtual-Real Interactive Smart Systems for "6S" Sensing

Yu Shen, Yuhang Liu, Yonglin Tian, *Member, IEEE* and Xiaoxiang Na, *Member, IEEE*

***Briefing*:** In the construction of Metaverses, sensors that are referred to as the "bridge of information transmission", play a key role. The functionality and efficiency of today's sensors, which operate in a manner similar to physical sensing, are frequently constrained by their hardware and software. In this research, we proposed the Parallel Sensing framework, which includes background, concept, basic methods and typical application of parallel sensing. In our formulation, sensors are redefined as the integration of real physical sensors and virtual software-defined sensors based on parallel intelligence, in order to boost the performance of the sensors. Each sensor will have a parallel counterpart in the virtual world within the framework of parallel sensing. Digital sensors serve as the brain of sensors and maintain the same properties as physical sensors. Parallel sensing allows physical sensors to operate in discrete time periods to conserve energy, while cloud-based descriptive, predictive, and prescriptive sensors operate continuously to offer compensation data and serve as guardians. To better illustrate parallel sensing concept, we show some example applications of parallel sensing such as parallel vision, parallel point cloud and parallel light fields, both of which are designed by construct virtual sensors to extend small real data to virtual big data and then boost the performance of perception models. Experimental results demonstrate the effective of parallel sensing framework. The interaction between the real and virtual worlds enables sensors to operate actively, allowing them to intelligently adapt to various scenarios and ultimately attain the goal of "*Cognitive*, *Parallel*, *Crypto*, *Federated*, *Social* and *Ecologic*" 6S sensing.

***Keywords*:** Parallel Sensing, Parallel Intelligence, CPSS, Metaverses, Virtual and Real Interaction, "6S" Sensing.

I. Introduction

NEAL Stephenson's science fiction novel "Snow Crash" from 1992 made the idea of the Metaverses, which emerged from Cyberspace and has received a lot of attention recently. "Metaverses" is made out of the two terms transcend and universe, respectively. The goal of Metaverses is to create virtual worlds that are parallel to the real world, conduct massive computational experiments, and interact with the real world for verification. Metaverses are built on the foundation of technologies like virtual reality [1], blockchain [2], cloud computing [3], and digital twins [4].

The idea of digital twins occupies a prominent position in the early stages. However, Metaverses and digital twins fall within the framework of parallel intelligence [5]. Digital twins are essentially the most basic parallel systems and their equivalents with a more systematic and scalable volume from Metaverses. Metaverses finally achieve parallel intelligence from a scientific and technological standpoint with the attainment of knowledge automation and intelligence. For example, when developing digital twins, we simulate physical systems are simulated, Moreover, researches mainly focus on cyber-physical systems (CPS), which are intelligent systems that tightly integrate computing, communication, and control in how they operate and interact with their task contexts. The digital twins are more likely an automated mirror system in the virtual world and rely on prior knowledge that input the systems, as a result, they are not so smart as wish, they typically operate in scenarios that follow particular rules. By including the human factors and adhering to the Cyber-Physical-Social Systems (CPSS) rule, Metaverses advance further since CPS is no longer suitable in expression against the background of intelligence [6]. The consideration of humans should not be neglected when describing intelligence, and the potential of an intelligent system to evolve continuously in order to expand and diversify its knowledge base is one of the characteristics of intelligence.

Sensors are essential infrastructures that serve as communication links between various worlds in order to build Metaverses and advance toward parallel intelligence. For instance, VR devices immerse us in the visual experience, while light field cameras enable us to collect 3D structural details for further 3D reconstructions. The majority of the sensors we utilize on a daily life, however, operate in a predetermined fashion and by predetermined criteria, making it hard for them to determine when to collect specific types of task-oriented data. The perception and decision-making processes of intelligent systems depend heavily on the quantity and

Corresponding author: Xiaoxiang Na.

Citation: Y. Shen, Y. H. Liu, Y. L. Tian, and X. X. Na, "Parallel Sensing in Metaverses: Virtual-Real Interactive Smart Systems for "6S" Sensing," *IEEE/CAA J. Autom. Sinica*, vol. 9, no. 12, pp. 2047–2054, Dec. 2022.

Y. Shen and Y. H. Liu are with School of Artificial Intelligence, University of Chinese Academy of Science, Beijing 100190, China (e-mail: shenyu2015@ia.ac.cn; liuyuhang2021@ia.ac.cn).

Y. L. Tian is with The State Key Laboratory for Management and Control of Complex Systems, Chinese Academy of Sciences, Beijing 100190, China (e-mail: yonglin.tian@ia.ac.cn).

X. X. Na is with Department of Engineering, University of Cambridge, Trumpington Street, CB2 1PZ, United Kingdom (e-mail: xnhn2@cam.ac.uk).

Digital Object Identifier: 10.1109/JAS.2022.106115

quality of the data, so it is essential to develop solutions for the design of smart sensors that will allow them to perform efficiently and intelligently.

Currently, simulation and popular simulators like Carla, Carsim, Apollo, Omniverse, Sumo, Prescan, Blender, and others are common methods to construct artificial systems. The simulation platform supports variable specifications of sensor suites, climatic conditions, and diverse scenes. Carla [7] is an open-source simulator that has been developed from the ground up to support the development, training, and validation of autonomous driving systems. A real-time cooperative design and simulation platform called Omniverse [8] was designed for Metaverses with the support of Nvidia's powerful graphic processing capabilities. Blender [9] is free open-source software that provides solutions for modeling, animation, rendering, and video creation. Blender's lightweight ray tracing function makes it suitable for light field research, and it is also one of its main advantages.

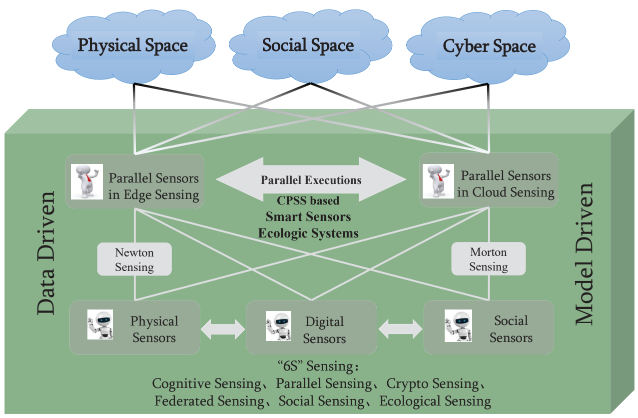

Fig. 1: Framework from Parallel Sensing to "6S" Sensing.

Based on the principle of parallel intelligence, we present a paradigm for parallel sensing in Metaverses in this paper. ACP, where A is for "Artificial Systems" in modeling, C is for "Computational Experiments" in analyzing, and P is for "Parallel Executions" in regulating, is the methodology that we employ in parallel sensing, which was originally introduced in 2017 [10]. The fundamental goal of ACP is to combine the "virtual" and "soft" elements of complex systems and turn them "hard" by using computational experiments that can be quantified and executed to address complicated issues in the real world. Artificial systems are virtual worlds that function similarly to real-world items in that they share the same physical, chemical, and other attributes, allowing them to operate under the same circumstances, the autonomous driving platform Carla can act as artificial systems with a diverse and vivid scenario and multiple virtual sensors with more flexibility than real sensors are used to collect large amount multi-modal data. Afterwards, numerous computational experiments can be carried out in the virtual environment once the artificial systems have been built. We are aware that in the age of deep learning, data quantity and quality play a crucial role in improving model performance. While real-world large-scale annotated data collection will necessitate a significant investment of time and resources, performing it in virtual worlds may be much cheaper. With the aid of artificial systems, we could generate enormous amounts of virtual data from small amounts of real-world data, train task-oriented models on the generated big data continually, and perform this in an iterative manner. In our parallel light field research, we build virtual camera arrays with adjustable baseline distances to adapt to different depth, in order to capture lights in different directions, the radius of the sphere for positioning the cameras is also tunable. Massive virtual efforts drive the meager real-world advancements and enormous computational experiments promote the transition from big data to deep intelligence.

This paper is organized as the following: Section II introduces the framework of "6S" sensing which is major feature of parallel sensing, Section III present brief description of parallel sensing which includes descriptive sensing systems, descriptive sensing systems, and prescriptive sensing systems and combined with the real system to constitute the whole parallel sensing systems. Section IV illustrated concrete implementation and applications of parallel sensing in vision, point cloud and light field researches that our team have conducted based on the methodology of parallel sensing.

II. Framework of "6S" Sensing

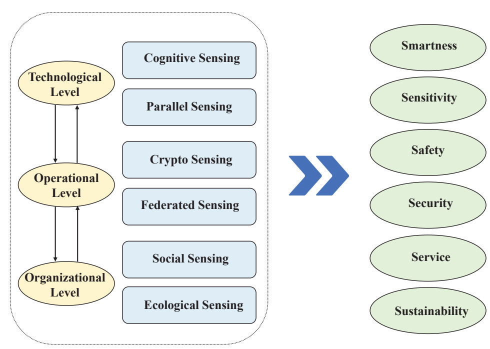

Fig. 2: Detail Illustration of "6S" Sensing.

Research on complex cyberspace systems, such as digital twins and Metaverses, has become increasingly important with the rapid development of XR and artificial intelligence technology. In the near future, Metaverses, which are the methodical evolution of digital twin systems, are promised to be extensively used in smart cities, intelligent industries, and entertainment. Nearly all applications share the fundamental characteristic of being tightly tied to sensing systems in both physical and virtual space. Sensing systems are crucial to the operation of complex systems because they serve as a connection between physical space and cyberspace as well as a means of bringing humans together in the actual world. While genuine sensing systems are intricately intertwined with human interaction and disclose prediction uncertainty, the current sensing systems are thought of as Newton systems that merely follow physical principles. Sensing systems in Metaverses should be regarded as Merton systems with the characteristic of self-actualization as long as taking into account human factors in social space. The ownership of a sensor in cyberspace is determined by the data acquired rather than the actual object, which is another key distinction between physical and digital sensing systems.

The security of sensing systems is very critical. Constructing a novel framework for 6S sensing that comprises safety index, security index, sustainability index, sensitivity index, service index, and smartness index is important due to the aforementioned flaw in modern sensing systems [11]. In this research, a brand-new intelligent sensing framework with "6S" sensing at three levels is proposed. At the technological level, it consists of cognitive sensing and parallel sensing, while on the operational level, crypto sensing and federated sensing should be considered and finally at the organizational level, social sensing and ecological sensing are critical components.

A. Cognitive Sensing

The goal of cognitive sensing is to imbue conventional physical sensors with human-like intelligence. Sensors are able to learn from the data they have already collected and generate predictions about incoming data in real time with the aid of neural networks, which are modeled upon human cognition [12]. In addition to accomplishing perception tasks, cognitive sensing focuses on grasping in-depth knowledge of perceptual outcomes and use them to make decisions for subsequent procedures, eventually endowing sensors with human cognition.

B. Parallel Sensing

A smart sensing system that takes into account social, virtual, and physical spaces is known as parallel sensing. It comprises of three types of sensing: descriptive sensing for modeling sensors in artificial systems, predictive sensing for conducting computational experiments with those systems, and prescriptive sensing for interacting with virtual and physical worlds. Parallel Sensing adheres to the "Small Data to Big Data to Deep Intelligence" [13] premise, which is explained in more detail in the following section.

C. Crypto Sensing

With a focus on data security in an uncertain and untrusted environment, blockchain-based crypto sensing provides a reliable assurance for the exchange of sensing data. Smart contracts in blockchain technologies are the specialized method for achieving crypto sensing, and decentralized autonomous organization (DAO) [14], [15] is the organizational structure of crypto sensing.

D. Federated Sensing

On the basis of federated learning, federated sensing realizes the transition from individual intelligence to swarm intelligence [16]. The current centralized training paradigm necessitates the aggregation of raw data, which raises concerns about security and privacy. The raw data from each sensor cannot be directly uploaded to the cloud for training due to concerns over data privacy. Each sensor in federated sensing merely needs to upload certain parameters of the locally trained model capable of swarm intelligence while maintaining data privacy.

E. Social Sensing

In cyber-physical-social systems (CPSS), social sensing focuses on how people behave in social settings. Human factors and social context are highlighted by CPSS in complex systems. Real-time social dynamic change can be observed through social sensing, which can also analyze for the best social decision and finally generate social knowledge. The abstract concepts used in social sensing for the interchange of social information, such as the cell phone, are intimately related to our daily lives.

F. Ecological Sensing

The observation and management issues with ecological systems are addressed through ecological sensing. At the organizational level, ecological sensing acknowledges the interdependence of social and natural sensing systems. Real-time environmental sensing, analysis, decision-making, and intelligent management capabilities enable it to realize the transition from the moral restraints of ecological systems to the legal constraints of social systems [17].

III. Parallel Sensing

Traditional physical sensing systems are insufficient to implement intelligent sensing at the technological level because of ignorance of cyberspace and social space. It is critical to develop a novel sensing framework that takes into account both physical and virtual sensing. A technical framework for intelligent sensing in Metaverses is proposed leveraging parallel sensing, which is based on parallel theory and the ACP methodology [18], [19]. Future sensing systems for the 6S index will utilize a special technology called parallel sensing. It includes advanced computing and communication technologies as well as rapidly developing artificial intelligence, such as XR and multi-modal perception, in addition to physical sensing technologies.

Data-driven descriptive sensing, experiment-driven predictive sensing, and interaction-driven prescriptive sensing make up parallel sensing. A closed-loop system that made up of these three components can operate continuously. Building artificial sensing systems in Metaverses is the objective of descriptive sensing, along with maintaining consistency between real-world and virtual sensor models. With the assistance of artificial systems, a quantity of synthetic data may be generated, which, along with smaller real data, makes up big data. Predictive sensing conducts computational experiments for various downstream tasks after building artificial sensing systems in cyberspace. Through computational experiments, it is able to accomplish the transition from small data to big data and then to deep intelligence and achieve the optimal strategy as expected.

A. Descriptive Sensing Systems

Traditional physical sensors lack the capability to process data locally and can merely collect data. Although embedded computing and distributed sensing are both developing rapidly, local computing power remains a significant barrier to the real-time implementation of intelligent sensing. With the support of virtual sensing, descriptive sensing is proposed for better management of sensing systems. It attempts to build digital sensing systems in the cloud that integrate both high-fidelity sensor models and the surrounding environment. In addition to the physical environment, social environments and human behaviors also have a significant impact on how well sensing systems operate [20]. Descriptive sensing is the pioneering work that takes into account of social environment with human factors and can be used to generate more realistic virtual data compared with simple digital twins' sensor models.

The fundamental application of descriptive sensing in cyberspace [21] is the generation of virtual data utilizing artificial systems. Before practical deployment, artificial sensing systems will be constructed, and each physical sensor will have an online digital counterpart. Unreal Engine and Omniverse, mature gaming and industrial engines, have already provided a number of sensor models and a framework for further development. Different digitization techniques are used for different sensor models, for example, ray tracing technology [22] is primarily employed for LiDARs whereas the scattering points method [23] is applied for mm-wave radars. These models can provide accurate synthetic data that is comparable to real data at a minimal expense, however, they disregard the internal structure of physical sensors, which has a significant impact on the fidelity of virtual data in complex scenes. Future sensor models will concentrate more on optimizing internal physical structures and principles. Additionally, due to their dependence on training scenarios, black-box-based sensor models [24], [25]inspired by end-to-end deep learning have only been utilized in academic research.

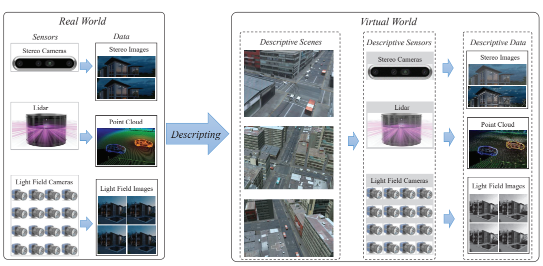

Fig. 3: Real to Virtual Descrptive Sensing.

NeRF [26], a novel 3D reconstruction technique, has the potential to be widely used to construct the physical environment in artificial systems and digital persons [27] to build the social environment. Future research should concentrate on the major issue of these technologies' high computing resource requirements. Descriptive sensing maintains consistency with physical sensing systems in practical application after the construction of artificial systems is complete and is solely in charge of the interaction of incremental data that can effectively reduce the burden on communication networks. The performance of trained models is now greatly influenced by data due to the development of data-driven deep neural networks. However, collecting data from actual scenarios is costly, and it is impossible to cover all the corner cases. Applying artificial sensing systems to provide synthetic data is an efficient method for addressing these issues. A massive amount of virtual data, critical for data-driven downstream tasks such object detection [28], [29], semantic segmentation [30], and self-localization [31], can be collected through descriptive sensing. Taking the widely used LiDAR sensor as an example, it has already been demonstrated that synthetic point cloud data can significantly improve model performance. Additionally, descriptive sensing can support the development of foundation models with improved generalization and the research of domain adaption in various scenarios.

B. Predictive Sensing Systems

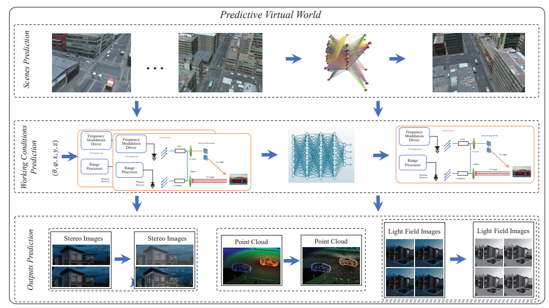

Fig. 4: Predictive Sensing in Virtual Worlds.

Descriptive sensing overlooks the dynamics of actual sensing systems even if it has already finished building artificial sensing systems on the cloud. Sensing systems should be regarded as Merton systems with the uncertainty of prediction since social space as well as human factors are involved. In order to conduct various computational experiments with artificial systems and also to make the transition from small data to big data and then to deep knowledge, predictive sensing is proposed in this context. The proposed algorithms' robustness may be enhanced through computational experiments, which can also provide the predicted optimal course of action.

In tasks requiring time and space dimensional predictions, predictive sensing exhibits significant advantages [32]. Predictive sensing may, in general, forecast how physical sensors will operate, identify potential issues before they occur, estimate crucial sensing regions, and produce non-critical data forecasts that can drastically cut on data transfer between the real and virtual world. To demonstrate the advantages of predictive sensing, examples of radars and light field cameras will be given since radars are essential for autonomous driving.

In addition to performing feature aggregation in time series for trajectory planning [33] and obstacle prediction tasks, predictive radars may also become aware of their surroundings through cooperative perception [34]. A distinctive type of camera with numerous tiny aperture lenses is light fields camera. It collects information of lights in the scene from every direction and completes post-processing afterwards. Predictive light field cameras can make predictions about the light field distributions in various positions by computational experiments in artificial systems, which can minimize the deployment of lenses in physical space.

C. Prescriptive Sensing Systems

The information transmission between physical and virtual systems is often disregarded in current research on virtual sensing systems, which focuses mostly on artificial systems and computational experiments by using ACP methodology. There will be a clear distinction between the way these two sensor systems operate, separate virtual sensing systems are not suitable for implementing smart sensing due to the environment's dynamics and complexity. Predictive sensing is proposed to establish a closed loop combining descriptive sensing and predictive sensing, which corresponds to parallel execution in the ACP methodology. Predictive sensing is an interactive intelligent software sensing system that employs deep knowledge obtained from computational experiments to take prescriptive control of sensing systems.

Traditional sensors mostly use analog circuits for signal generation and processing, however, due to the high noise and weak anti-interference ability of analog circuits, it is challenging to take precise control of sensors in real time. As digital technologies advances, prescriptive sensing has the potential to control physical sensing systems intelligently, enabling sensors to adapt to more complex environments. Different waveform types provide advantages for the commonly used LiDAR sensors. For instance, pulse waveforms can achieve high precision at a low cost whereas frequency-modulated continuous waveforms can offer additional information on Doppler velocity. Prescriptive sensing may effectively increase the performance of sensors through dynamically adjusting the waveform mode in accordance with the environment through the use of digital waveform generation. To collect data from light field cameras, which contains a lot of redundant information, numerous lenses must operate simultaneously. Prescriptive sensing can assist in maintaining the same effect with the deployment of only a portion of lenses in crucial areas, reducing the waste of hardware resources.

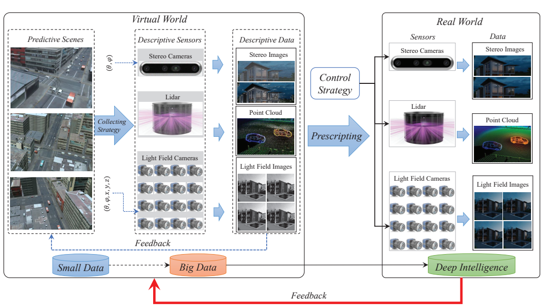

Fig. 5: Virtual to Real Prescriptive Sensing.

IV. Implementation of Parallel Sensing

Parallel intelligence theory has been applied in a variety of areas since Prof. Fei-Yue Wang first outlined it in 2004. These various applications ranging from sensors to intelligent transportation, computer vision, agriculture, and education. We will give a thorough introduction to our teams' parallel sensing applications in parallel vision, parallel point clouds, and parallel light fields in this section.

A. Parallel Vision

Parallel vision is a computing paradigm that integrates computer graphics, virtual reality, machine learning, and knowledge automation. It was first proposed by Wang in 2017 and is based on the ACP approach. One of the objectives of parallel vision is to evaluate the performance of algorithms in various complex environments. For instance, some vision algorithms are trained on sunny bright highway scenarios; it is obviously impossible to deploy them directly in rainy, snowy, or foggy weathers with lower illumination and occlusions that may lead to perception failures. As big data technology has advanced, numerous researchers have contributed to the dataset creation process, such as KITTI for autonomous driving, CoCo for object detection, and large scale ImageNet for pretraining. Perception algorithms are currently trained for specific tasks on a single or small collection of datasets; however, the obtained models are difficult to directly transfer due to domain differences. Parallel vision emerged in these conditions, attempting to address these issues of different data collection and calibration.

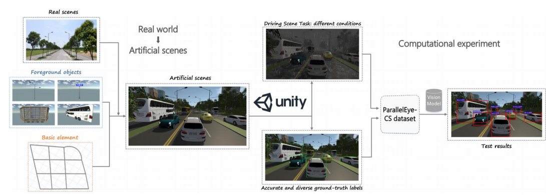

Fig. 6: Pipline of Generating and Utilizing ParallelEye-CS for Vehicle Intelligence Testing [35].

Photo-realistic artificial scenes are used to represent and simulate complex scenes in parallel vision [36], where sensors are generalized software defined devices that can perceive their environments and output data in the form of images. Computational experiments are then conducted to train and verify various vision models, and finally vision systems are optimized online with the operation of parallel executions. ParallelEye-CS [35], a system designed for visual simulation testing in autonomous driving, is an implementation of a parallel vision application. In Changshu, China, where the 2013-2018 Intelligent Vehicle Future Challenge (IVFC) was held, Paralleleye was built in accordance with the prototype. As shown in Fig. 6, the real-world testing field roadmap and a variety of foreground and background scenes were created in the simulation engine Unity. They use OpenStreetMap (OSM) open-source geographic data to construct the basic road network in virtual worlds. Scenes like tunnels, bridges, interstate highways, and country roads with different weather conditions can be tailored using the CityEngine software. They developed realistic traffic signs, street lights, doorplates, and buildings using 3ds Max. The Unity3d engine also simulates scene dynamics, and virtual cameras capture the entire scenes. The ParallelEye-CS dataset has a total of 17450 frames (virtual training data with 3650 frames, normal tasks with 5520 frames, environmental tasks with 4140 frames, and difficult tasks with 4140 frames). The main benefit is its flexibility in weather and scene customization, small data in the real world can be expanded to big data in the virtual world, and the generated virtual big data are then used to train different vision models for different perceptions.

B. Parallel Point Clouds

As autonomous driving technology has advanced, LiDAR has taken over as the standard range detecting sensor. A LiDAR device can measure the precise distances between itself and its surroundings. LiDAR can be categorized into mechanical and solid types depending on whether a moving rig is available. The vertical emission unit, also known as the harness, ranges from 1 to 128 and determines the accuracy of LiDAR, more harness implies denser points. Compared to camera devices, LiDAR can accurately record 3D structural information, particularly the depth, nevertheless, deployment and calculation are challenging due to the high value and disorder of the point clouds. Previous to object detection in autonomous driving, LiDAR point clouds should be preprocessed with denoising, inpainting, and other procedures, however, these operations severely hamper real-time requirements. On the other hand, point cloud annotation presents another challenge since a single point has no meaning. Tian [37] proposed the Parallel Point Clouds framework trying to find a solution to these issues.

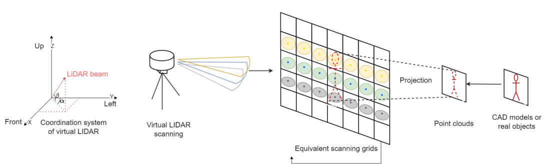

Fig. 7: The Illustration of Virtual Point Cloud Generation Pipeline [37].

A 360-degree scanning virtual LiDAR was first designed as the virtual sensor in parallel point clouds. A virtual LiDAR can provide the same horizontal and vertical resolution as a real LiDAR by replicating its mechanism. LiDAR beams are encoded by a two-dimensional index [*i*, *j*] as shown in Fig. 7, where i is the beam's id in the vertical dimension and j is the beam's id in the horizontal dimension. Virtual LiDAR Field of View can be acquired by substituting virtual LiDAR resolutions r_v and r_h in the vertical and horizontal directions, respectively. The minimum angle in the vertical and horizontal directions is denoted as α_0 and β_0 accordingly. virtual LiDAR Field of View can be acquired as:

$$\alpha_{i,j} = \alpha_0 + i \times r_v \tag{1}$$

$$\beta_{i,j} = \beta_0 + j \times r_h \tag{2}$$

with the spherical projective methods, homogeneous coordinates of points with a distance of l_0 to the sensor can be obtained as $P_{i,j} = [x_{i,j}, y_{i,j}, z_{i,j}, 1]$, then following the rule of perspective projection, 3D points $P_{i,j}$ are projected to image planes as:

$$\hat{P_{i,j}} = KC_w P_{i,j}^T \tag{3}$$

Up until now, data collection has been achievable using a simulated LiDAR sensor. Since object distribution varies across scenes and frames, another characteristic of parallel point clouds is data customization. To fully boost the accuracy of perception algorithms, we can augment point cloud data through adding automobiles or pedestrians in frames using enormous free 3D models. The iPad Pro is a very useful mobile device for scanning and obtaining object models, for instance, surface points can be acquired for CAD models using surface points sampling methods. Subsequently, the clean backgrounds are then supplemented with a variety of foreground objects to produce rich and diverse traffic scenarios.

A hybrid point cloud dataset called ShapeKitti was proposed employing Kitti and ShapeNet as sources of actual and virtual point clouds, respectively. The configurations of the virtual LiDAR are listed in Table I. A total of 3712 samples from the Kitti dataset and 200 car models from ShapeNet are used as clean backgrounds and foregrounds, respectively. According to results showing 78.6% and 86.8% of the performance of the models trained with real Kitti for 3D and BEV precision, respectively, the PointPillars and SECOND object detection models were trained on ShapeKitti for 20 epochs to evaluate the performance of the ShapeKitti dataset on real-time 3D detectors. For a dataset that requires almost minimal human annotations, this is a very encouraging outcome.

C. Parallel Light Fields

Light field cameras are less widely recognized than regular cameras as vision sensors. Unlike regular cameras, which can only capture light intensity and object appearance, light field cameras can additionally implicitly record the scene's depth and the rays' directions. Light field cameras capture scenes as 5D image sets of the pattern $A \times A \times H \times W \times C$, where A, H, W and C are angular resolution, image height, image width, and image channels respectively, and angular resolution corresponds to sub camera in camera arrays. By disentangling light field images from angular and spatial domains, we can obtain angular and spatial features with feature extractors and fuse them to recover 3D structures finally. Light field cameras are still less common than LiDARs despite the benefits of 3D structural information, perhaps this is due to the high cost and difficulties in calibrations. Without any mechanical tuning modules, it is impossible to adjust light field cameras and make them task-oriented once they have been manufactured. The current technical framework of light field cameras primarily consists of three types: microlens arrays, camera arrays, and encoded masks. For instance, in order to perceive scenarios with different depths, we must adjust the baseline distances between adjacent cameras in the form of a linear or exponential function. We can also change the radiance of the camera sphere to capture lights from different angles, however, these situations are impossible to achieve in real light fields. On the other hand, light field images are challenging to obtain and the small volume of the available datasets greatly limit their potential to completely boost the performance of the existing perception models.

Our team proposed the Parallel Light Fields framework to address the aforementioned issues [38]–[40]. In parallel light

TABLE I: The configurations of the virtual scanning grids.

Attribute	H-Resolution (Channels)	V-Resolution	H-FoV	V-FoV	Detection Range
Value	0.4(64)	0.2	[-45,45]	[-24.8,2]	120m

TABLE II: The configurations of the virtual light fields.

Focal Length	Baseline Distances	Sensor Size	Image Size	Angular Resolution
39mm	0.125	36mm	1024×1024	9×9

fields, we continue to employ the ACP approach pipeline and the opensource Blender platform to construct our virtual environment. Since there are so many free 3D models available online, we can quickly and easily generate our photo-realistic artificial systems. We could freely define our virtual light field camera in Blender thanks to the python API. In our settings, we adopt the scheme of camera arrays and the tunable parameters are listed as in table II.

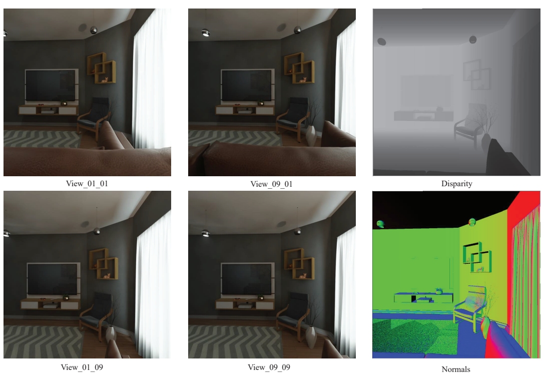

Fig. 8: The Rendered Light Field Images Based on Parallel Light Fields.

After the creation of virtual light field cameras and virtual scenes, light sources are a critical element. Blender provides four different types of light sources, including dot, spot, sunlight, and area, from which we may select the one that best suits our needs. As till right now, the environment for capturing light field images is complete. We can switch to light field cameras to collect 5D images, and we can achieve ground truth measurements like segmentation, normals, depth, and disparities. We can also record optical flow as a gauge for dynamic situations. As far as we known, this is the first dataset in light field research that can be used for so many different objectives. However, with more angular views, there is an additional problem of data redundancy; specifically, diverse views serve as compensation information and also result in view overlap, which is the source of redundancy. We discover that baseline distances between adjacent cameras have a relationship with data redundancy, an adaptive baseline distance may achieve a balance between data redundancy and computational efficiency. We can perform a great deal of computational experiments in the context of parallel light fields, small data can be expanded into big data to train perception models, and the abstracted knowledge may help guide the placement of actual light field cameras and create an interactive, iterative optimization closed-loop.

V. Conclusion

Based on the theory of parallel intelligence, we introduce the concept of parallel sensing in this paper. Virtual descriptive sensors in the virtual worlds are digital twins of the real-world sensors with the same features and are utilized to interact with the virtual environment to expand real small data to virtual big data. Artificial systems will be built as the testbed for parallel sensing. After that, different perception models and deductive reasoning are learned using the generated big data and applied to real-world sensors. Physical sensors are guarded by three counterparts known as descriptive, predictive, and prescriptive sensors. We expand the capabilities of sensors beyond their function as a tool for data acquisition by regarding them from three perspectives: cognitive and parallel sensing in terms of intelligence, crypto and federated sensing in views of safety, and social and ecologic sensing from the perspective of society to pace towards the "6S" sensing.

Acknowledgment

The authors would like to thank Prof. Fei-Yue Wang for his ground-breaking work on the parallel system theory employed in this paper, and for constructive comments and insightful ideas that have greatly improved this paper.

This work was supported by the National Key R&D Program of China (2018AAA0101502) and the Science and Technology Project of SGCC (State Grid Corporation of China): Fundamental Theory of Human-in-the-Loop Hybrid-Augmented Intelligence for Power Grid Dispatch and Control.

References

[1] G. C. Burdea *et al.*, *Virtual reality technology*. John Wiley & Sons, 2003.

[2] M. M. Hassan *et al.*, "Guest Editorial for Special Issue on Blockchain for Internet-of-Things and Cyber-Physical Systems," *IEEE/CAA Journal of Automatica Sinica*, vol. 8, no. 12, p. 1867, 2021.

[3] T. Dillon *et al.*, "Cloud computing: issues and challenges," in *2010 24th IEEE international conference on advanced information networking and applications*. IEEE, 2010, pp. 27–33.

[4] Q. Wang *et al.*, "Digital Twin for Human-Robot Interactive Welding and Welder Behavior Analysis," *IEEE/CAA Journal of Automatica Sinica*, vol. 8, no. 2, pp. 334–343, 2021.

[5] X. Wang *et al.*, "Acp-based social computing and parallel intelligence: Societies 5.0 and beyond," *CAAI Transactions on Intelligence Technology*, vol. 1, no. 4, pp. 377–393, 2016.

[6] F.-Y. Wang *et al.*, "Parallel driving in CPSS: A unified approach for transport automation and vehicle intelligence," *IEEE/CAA Journal of Automatica Sinica*, vol. 4, no. 4, pp. 577–587, 2017.

[7] A. Dosovitskiy *et al.*, "CARLA: An open urban driving simulator," in *Conference on robot learning*. PMLR, 2017, pp. 1–16.

[8] Z. Song *et al.*, "Omniverse-opends: Enabling agile developments for complex driving scenarios via reconfigurable abstractions," in *International Conference on Human-Computer Interaction*, 2022.

[9] B. R. Kent, *3D scientific visualization with blender*. Morgan & Claypool Publishers San Rafael, CA, USA, 2015.

[10] F.-Y. Wang, "Parallel Sensing and Parallel Blockchain for Transportation 5.0: From RFID to IoT for ITS in CPSS," in *The 11th Annual IEEE International Conference on RFID*. IFAC, 2017.

[11] X. Li *et al.*, "From features engineering to scenarios engineering for trustworthy AI: I&I, C&C, and V&V," *IEEE Intelligent Systems*, vol. 37, no. 4, pp. 18–26, 2022.
[12] H. Lu *et al.*, "Guest editorial for special issue on cognitive computing for collaborative robotics," *IEEE/CAA Journal of Automatica Sinica*, vol. 8, no. 7, p. 1221, 2021.
[13] F.-Y. Wang *et al.*, "Steps toward parallel intelligence," *IEEE/CAA Journal of Automatica Sinica*, vol. 3, no. 4, pp. 345–348, 2016.
[14] S. Wang *et al.*, "Decentralized autonomous organizations: Concept, model, and applications," *IEEE Transactions on Computational Social Systems*, vol. 6, no. 5, pp. 870–878, 2019.
[15] F.-Y. Wang, "The engineering of intelligence: DAO to I&I, C&C, and V&V for intelligent systems," *The International Journal of Intelligent Control and Systems*, vol. 1, no. 3, pp. 1–5, 2021.
[16] L. Li *et al.*, "A review of applications in federated learning," *Computers & Industrial Engineering*, vol. 149, p. 106854, 2020.
[17] F.-Y. Wang *et al.*, "Parallel ecology for intelligent and smart cyber–physical–social systems," *IEEE Transactions on Computational Social Systems*, vol. 7, no. 6, pp. 1318–1323, 2020.
[18] F.-Y. Wang, "Parallel system methods for management and control of complex systems," *CONTROL AND DECISION.*, vol. 19, pp. 485–489, 2004.
[19] Y. Liu *et al.*, "Metaradars: Acp-based intelligent radar systems in metaverses," *Journal of Intelligent Science and Technology*, vol. 2, no. 1, pp. 12–17, 2022.
[20] J. Mei *et al.*, "Incorporating human domain knowledge in 3-d lidar-based semantic segmentation," *IEEE Transactions on Intelligent Vehicles*, vol. 5, no. 2, pp. 178–187, 2020.
[21] E. Asher *et al.*, "Methods and models for simulating autonomous vehicle sensors," *IEEE Transactions on Intelligent Vehicles*, vol. 5, no. 4, pp. 684–692, 2020.
[22] T. Hanke *et al.*, "Generation and validation of virtual point cloud data for automated driving systems," in *2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC)*. IEEE, 2017, pp. 1–6.
[23] J. Thieling *et al.*, "Scalable and physical radar sensor simulation for interacting digital twins," *IEEE Sensors Journal*, vol. 21, no. 3, pp. 3184–3192, 2020.
[24] T. A. Wheeler *et al.*, "Deep stochastic radar models," in *2017 IEEE Intelligent Vehicles Symposium (IV)*. IEEE, 2017, pp. 47–53.
[25] R. Weston *et al.*, "There and back again: Learning to simulate radar data for real-world applications," in *2021 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2021, pp. 12 809–12 816.
[26] B. Mildenhall *et al.*, "NeRF: Representing scenes as neural radiance fields for view synthesis," *Communications of the ACM*, vol. 65, no. 1, pp. 99–106, 2021.
[27] W. Zhu *et al.*, "Applications and research trends of digital human models in the manufacturing industry," *Virtual reality & intelligent hardware*, vol. 1, no. 6, pp. 558–579, 2019.
[28] I. Ahmed *et al.*, "Towards collaborative robotics in top view surveillance: A framework for multiple object tracking by detection using deep learning," *IEEE/CAA Journal of Automatica Sinica*, vol. 8, no. 7, pp. 1253–1270, 2021.
[29] Y. Tian *et al.*, "Training and testing object detectors with virtual images," *IEEE/CAA Journal of Automatica Sinica*, vol. 5, no. 2, pp. 539–546, 2018.
[30] W. Li *et al.*, "Aads: Augmented autonomous driving simulation using data-driven algorithms," *Science robotics*, vol. 4, no. 28, p. eaaw0863, 2019.
[31] P. Gao *et al.*, "Dc-loc: Accurate automotive radar based metric localization with explicit doppler compensation," in *2022 International Conference on Robotics and Automation (ICRA)*. IEEE, 2022, pp. 4128–4134.
[32] K. Nima *et al.*, "Real-time driver maneuver prediction using lstm," *IEEE Transactions on Intelligent Vehicles*, vol. 5, no. 4, pp. 714–724, 2020.
[33] W. He *et al.*, "Modeling and trajectory tracking control for flapping-wing micro aerial vehicles," *IEEE/CAA Journal of Automatica Sinica*, vol. 8, no. 1, pp. 148–156, 2021.
[34] Y. Shen *et al.*, "Radar foundation models towards natural interactions and smart operations of radar systems," *The International Journal of Intelligent Control and Systems*, vol. 2, no. 1, pp. 11–16, 2021.
[35] X. Li *et al.*, "Paralleleye-cs: A new dataset of synthetic images for testing the visual intelligence of intelligent vehicles," *IEEE Transactions on Vehicular Technology*, vol. 68, no. 10, pp. 9619–9631, 2019.
[36] K. Wang *et al.*, "Parallel vision for perception and understanding of complex scenes: methods, framework, and perspectives," *Artificial Intelligence Review*, vol. 48, no. 3, pp. 299–329, 2017.
[37] Y. Tian *et al.*, "Parallel point clouds: Hybrid point cloud generation and 3d model enhancement via virtual–real integration," *Remote Sensing*, vol. 13, no. 15, p. 2868, 2021.
[38] F.-Y. Wang and Y. Shen, "Parallel light field: A perspective and a framework," *IEEE/CAA Journal of Automatica Sinica*, vol. 9, no. 11, pp. 1871–1873, 2022.
[39] F.-Y. Wang, "Parallel light field and parallel optics, from optical computing experiment to optical guided intelligence," The State Key Laboratory for Management and Control of Complex Systems, Tech. Rep., 2018. [Online]. Available: http://www.sklmccs.ia.ac.cn/2018reports.html
[40] F.-Y. Wang *et al.*, "Parallel light field: the framework and processes," *Chinese Journal of Intelligent Science and Technology*, vol. 3, no. 1, pp. 110–122, 2021.

Yu Shen received his master's degree in University of Chinese Academy of Science. He is currently pursuing the Ph.D. degree in School of Artificial Intelligence, University of Chinese Academy of Science. His research includes parallel light fields, neural rendering light fields, 3D reconstruction and optical flow estimation.

Yuhang Liu received the B.S. degree in Department of precision instrument, Tsinghua University, in 2021. He is currently pursuing the Ph.D. degree in School of Artificial Intelligence, University of Chinese Academy of Science. His current research focuses on parallel sensing, 3D object detection and point cloud data generation.

Yonglin Tian received his Ph.D. degree in control science and engineering from the University of Science and Technology of China in 2022. He is currently a post-doctoral researcher at the State Key Laboratory for Management and Control of Complex Systems, Chinese Academy of Sciences. His research interests includes computer vision and intelligent transportation systems.

Xiaoxiang Na received the Ph.D. degree in driver-vehicle dynamics from the Department of Engineering, University of Cambridge, U.K. in 2014. He is currently a Senior Research Associate with the Centre for Sustainable Road Freight, University of Cambridge, and a Borysiewicz Interdisciplinary Fellow at the University of Cambridge. His main research interests include operational monitoring of road freight vehicles, vehicle energy performance assessment, and driver-vehicle dynamics.