

Crowd Sensing Intelligence for ITS: Participants, Methods, and Stages

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Abstract—The construction of transportation 5.0 or the so-called society-centered intelligent transportation systems (ITS) has aroused higher requirements for the intelligent sensing capability to seamlessly integrate Cyber-Physical-Social Systems (CPSS). Crowd Sensing Intelligence (CSI), as a promising paradigm, leverages the collective intelligence of heterogeneous sensing resources to gather data and information from CPSS. Our first Distributed/Decentralized Hybrid Workshop on Crowd Sensing Intelligence (DHW-CSI) has been focused on principles and high-level processes of organizing and operating CSI. This letter reports the discussion results of the second DHW-CSI addressing the participants, methods, and stages of CSI for ITS. We categorized sensing participants into three kinds, i.e., biological, digital, and robotic. Then we summarized three methods to enable sensing intelligence, i.e., foundation models, scenarios engineering, and human-oriented operating systems. Finally, we anticipated that the progression of CSI will experience three stages, from algorithmic intelligence to linguistic intelligence, and eventually to imaginative intelligence.

Index Terms—Crowd sensing intelligence, Intelligence transportation systems, Cyber-physical-social systems

I. INTRODUCTION

WITH the rapid advancement of the Internet of Things (IoT) and social media, coupled with the widespread use of mobile devices, vast amounts of data are being generated almost instantaneously from not only physical space but also cyber and social spaces [1]. Big data presents opportunities for developing efficient, safe, smart, reliable, and sustainable ITS [2], and the social signals contained within big data are driving the transformation of traditional transportation systems towards Transportation 5.0 [3]. To fully grasp the dynamic characteristics of Transportation 5.0 and enable the ITS to offer more smart services, a suite of intelligent sensing schemes is demanded to organize massive sensing resources and acquire high-quality data from different spaces of Transportation 5.0 [4], [5].

Manuscript received May 5, 2023; revised May XX, 2023; accepted May XX, 2023. This study is supported by the National Natural Science Foundation of China (62202477, 62173337, 21808181, 72071207), and Humanity and Social Science Youth Foundation of Ministry of Education of China (19YJCZH073). (Yong Zhao and Cong Hu contributed equally to this work.) (Corresponding author: Peng Jiao and Fei-Yue Wang).

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Over the past decade, crowd sensing has emerged as a promising sensing pattern that leverages the collective intelligence of humans and organizations [6]. Similar to concepts such as spatial crowdsourcing and human flesh search [7], a traditional crowd sensing campaign consists of many micro sensing tasks. These micro tasks are supposed to be completed by human participants equipped with mobile devices. To this end, various task assignment strategies and incentive mechanism designs have been proposed to improve the task performance. With the deep integration of CPSS, the collaborative fusion of humans, machines, and IoT has become an emerging trend [8]. This requires a powerful and generic intelligence for crowd sensing, that organizes and plans sensing resources across different spaces, such as intelligent vehicles [9]–[11] in physical space, web crawlers in cyber space, and humans in social space. This trend leads to a new generation of crowd sensing and the formation of Crowd Sensing Intelligence (CSI).

Several DHWs on different issues were held before, such as DHW on Sustainability for Transportation and Logistics (DHW-STL) [12], [13], DHW on Autonomous Mining (DHW-AM) [14], DHW on Ethics, Responsibility, and Sustainability (DHW-ERS) [15], and DHW on Data Science for Intelligent Vehicles (DHW-DSiV) [16]. To achieve CSI and to take a big leap toward ITS, Professor Fei-Yue Wang and associate editor Bin Chen launched the Distributed/Decentralized Hybrid Workshop on Crowd Sensing Intelligence (DHW-CSI). The discussion of our first DHW-CSI was reported before concerning the principles and high-level processes of organizing and operating CSI [10]. The second DHW-CSI was held on March 15, 2023, which addressed the participants, methods, and stages of CSI for ITS, as illustrated in Fig. 1.

The participants of CSI are categorized into three kinds: biological, digital, and robotic participants, which are resources to complete sensing tasks. To enhance CSI and guide these participants, we summarized three methods as shown in the middle layer of Fig. 1. Foundation models [17] have strong capabilities to solve various downstream sensing tasks, and can be recognized as the core of CSI. Scenarios engineering [18] performs fine-tuning and validation of foundation models in specific scenarios to guarantee the visibility, interpretability, and reliability of CSI. Furthermore, the CSI powered by foundation models and scenarios engineering is integrated within the Human-Oriented Operating Systems (HOOS) [19], achieving efficient communication and interaction between CSI and participants. The three methods will promote the progression of CSI which will experience three stages, as shown in the bottom layer of Fig. 1. Currently, CSI is marching

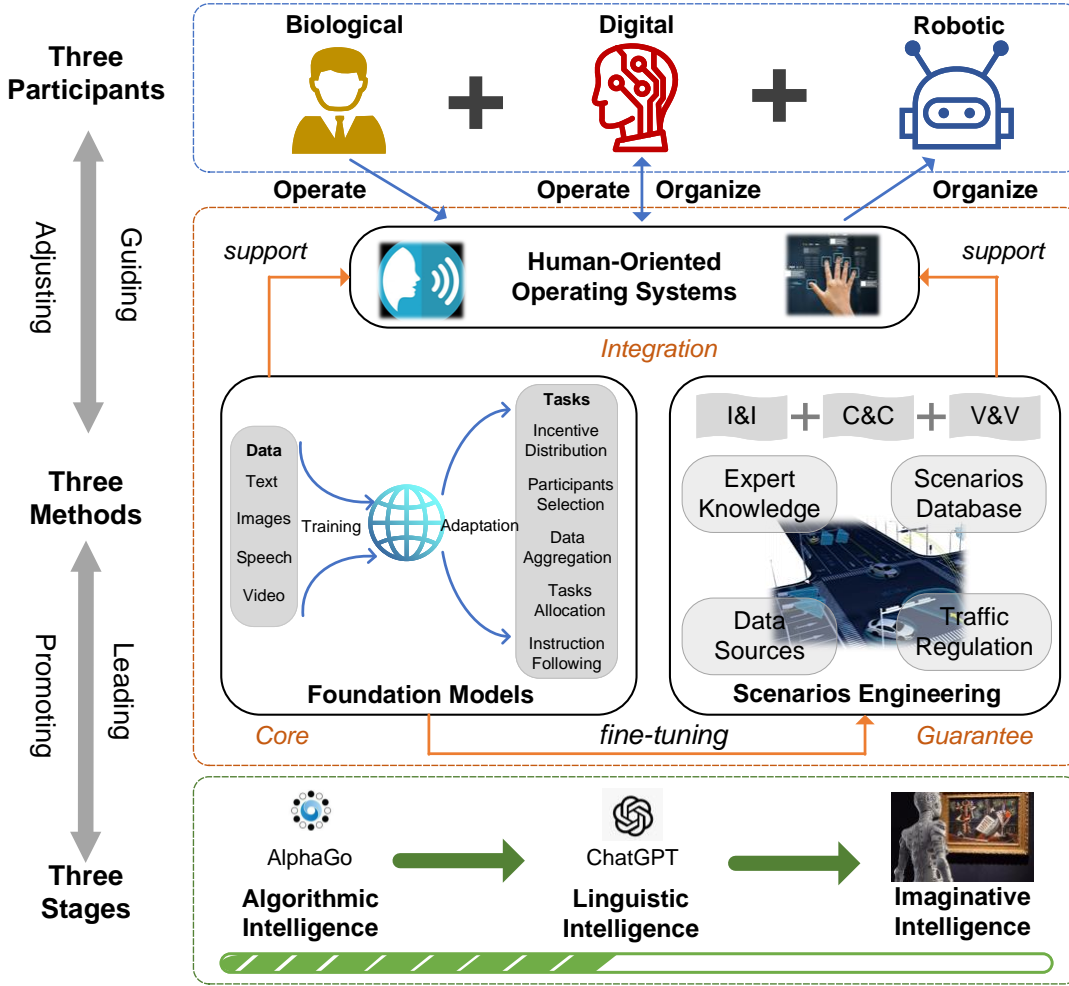


Fig. 1. Participants, methods, and stages of Crowd Sensing Intelligence

from algorithmic intelligence to linguistic intelligence, with the emergence of ChatGPT [20], and aiming toward imaginative intelligence.

II. THREE KINDS OF PARTICIPANTS OF CSI

To deconstruct the complexity of human and social factors in CPSS, parallel intelligence [21] is widely implemented, resulting in the categorization of three kinds of humans: biological humans, digital humans, and robotic humans [22]–[25]. Digital humans and robotic humans are the counterparts of biological humans in cyber and physical spaces, respectively, and can perform the majority of the physical and mental work instead of biological humans. Wang believes that digital workers will make up about 80% of the future workforce in Industries 5.0, while robotic workers and biological workers will account for about 15% and 5%, respectively [26]. The cooperation of the three kinds of humans enables various activities in CPSS, such as art creation [27], manufacturing [24], driving [22], and management [28] while ensuring the realization of the 6S goals: safety, security, sustainability, sensitivity, service, and smartness [23].

Guided by parallel intelligence [29], crowd sensing intelligence can be investigated, in which three kinds of participants

(i.e., digital, robotic, and biological) coexist and coordinate to form a more reliable and intelligent sensing pattern, as shown in Fig. 2. Digital participants are the generalized embodiment of AI programs, Apps, digital assets, and other elements that mainly active in cyber space without physical entities. They play an important role in sensing activities, such as collecting data in cyber space, making sensing plans and other computation tasks, providing guidance for robotic and biological participants, enabling incentive distribution, etc. Robotic participants are essentially the upgrades of ubiquitous sensing nodes driven by IoT, which have more intelligence and autonomy to replace biological humans in completing sensing tasks. For example, various intelligent vehicles [9], [10] are the ideal robotic participants for sensing traffic states. Biological participants refer to the humans involved in crowd sensing, and their productivity and efficacy are optimized through the assistance offered by digital and robotic participants.

The three kinds of participants work cooperatively. When receiving sensing requirements, digital participants make sensing plans instead of biological participants, including task assignment and participant selection, and continuously refine the plans through computational experiments in the artificial system. Digital participants carry out sensing tasks in

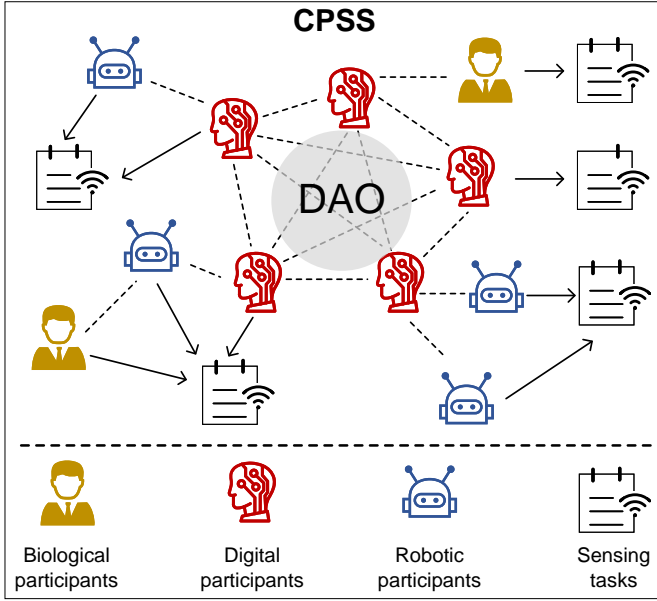


Fig. 2. Three kinds of participants of CSI

cyberspace while simultaneously guiding robotic participants to complete tasks in physical space. When either of them commits errors or fails to complete the tasks, biological participants may intervene in the sensing activity, such as collecting data personally or modifying sensing plans. Due to the comprehensive abilities of a human, sensing tasks in different spaces can all be completed by biological participants. The abilities of three kinds of participants are enhanced in the process of cooperation. Biological participants serve as tutors for digital and robotic participants to emulate and learn from. Besides, the performance of digital and robotic participants is evaluated in sensing-related activities so that they can continuously improve and eventually evolve into companions that cater to the personalized needs of biological participants.

In the cooperative sensing process of the three kinds of participants, a large number of data exchanges, information transmission, and incentive distribution need to be implemented, which pose great challenges to organizing and managing numerous participants while also preserving their privacy. The gaming method for multi-agent is a promising method to conquer these challenges [30]. Moreover, the rapid development of Decentralized Autonomous Organizations (DAO) [31] in recent years has provided a useful framework to promote the decentralized collaboration of participants. Digital participants, as the center of the sensing process, are organized into the DAO-based community, in which the rules of management and operation are encoded on the blockchain in the form of smart contracts. Without the intervention of the third party, the community can realize self-operation, self-government, and self-evolution according to the preset rules, to realize the maximum efficiency and value circulation of the community. Moreover, the token economy based on the blockchain can be used to implement incentive distribution.

III. THREE TECHNIQUES TO IMPLEMENT

Most previous research on crowd sensing has focused solely on specific steps within the sensing process, such as participant recruitment, task allocation, incentive distribution, and privacy preservation. Therefore, specific algorithms or models were designed to solve well-segmented problems under certain assumptions. As a result, these algorithms focused on theoretical models, but we can hardly see studies investigating practicality or empirical studies in the real world. Therefore, we summarized three methods to enable CSI and promote its practical implementation.

A. Foundation models: the core of intelligence

Foundation models appear as the paradigm shift with the rise of models trained on broad data (generally using self-supervision at scale) that can be adapted to a wide range of downstream tasks [17]. Since foundation models usually have a large number of parameters (with up to 200 billion [32], and even reaching a trillion [33]), researches working on foundation models are mainly led by big tech companies [34]. So far, foundation models have achieved impressive performance in vision, language, multimodal domains, and etc. The ChatGPT, a large language model belonging to the foundation models family, has aroused significant attention from researchers worldwide recently [19], [35], [36].

Foundation models provide potential benefits of fusing all the related data and customizing tasks of the entire crowd sensing process across multiple modes. Supported by foundation models, current research on crowd sensing for ITS will witness the transition from limited, isolated, particular, and feature-based algorithm design towards strong, united, general, and scenario-based intelligence emergence. By now, there are only a few researches on foundation models in the context of ITS. Zhao et al. [37] proposed the TengYun, as the foundation models developed by parallel learning and federated intelligence. It can provide feasible solutions for a wide range of scenarios in TransVerse (transportation metaverse), and help TransVerse to adapt the complex dynamic in real-world traffic scenarios. This work inspires us to develop the foundation models-powered CSI for ITS. By integrating all-sided functions to provide smart solutions for various tasks in crowd sensing with a single model, foundation models will be recognized as the core of intelligence. Since the sensing process involves numerous and heterogeneous sensing entities and tasks in different spaces, the foundation models-powered CSI is expected to integrate cyber, physical, and social spaces, human and machine intelligence, and artificial and actual systems to better counter the uncertainty and dynamic nature in the real world.

B. Scenarios engineering: the guarantee of trustworthy and interpretable intelligence

Foundation models are qualified for a wide range of downstream tasks, but the direct use of foundation models in specific domains or scenarios often has a certain gap. For example, they sometimes export biased, unreliable, spurious, and even

dangerous content. The negative comments such as “Bullshit spewer” [38] and “Jack of all, master of none” [39] on GPT-3 and ChatGPT reveal the deficiency of current foundation models. Therefore, to guarantee the trustworthiness and interpretability of CSI based on foundation models, scenario-oriented fine-tuning is essential, in addition to large-scale pretraining.

Scenarios engineering can shape the CSI to be a form that is more relevant to the underlying scenarios that will be learned and tested [18], and it includes six key dimensions: Intelligence and Index (I&I), Calibration and Certification (C&C), and Verification and Validation (V&V). With the help of I&I, C&C, and V&V, CSI will be continuously calibrated and verified for its dynamic functioning. The earliest application of scenarios engineering can be traced back to the Apollo 13 rescue mission, although the term “scenarios engineering” was not coined at that time [34]. Up to time now, scenarios engineering is always combined with foundation models to achieve the journey toward trustworthy AI. In industrial systems, scenarios engineering was integrated with field foundation models *EuArtisan* to improve machine intelligence while ensuring industrial interpretability and reliability [40]; Li et al. [34] developed a theoretical framework of scenarios engineering for building accessible and reliable foundation models in the metaverse; Scenarios engineering was also fused with management foundation models to provide provable security and flexible scalability management solution [28].

The validation in previous works of crowd sensing was usually carried out based on simulated or real-world datasets. However, it is difficult to find all data needed for research in a single data set. Therefore, an alternative solution is always adopted in that expected data are extracted from different data sets. For example, in the research on mobile crowd sensing [41], the targeted sensed data and the users’ mobility data are independent and come from different data sets. These data sets are scattered, sparse, and even generated on different spatiotemporal scales. In addition, the data sets are static and fixed, which cannot reflect the uncertainty and dynamic in the real sensing scenarios. This causes a gap between the research and the practical implementation of CSI.

Guided by parallel intelligence and scenarios engineering, we can establish a scenarios base in the form of a parallel system, including sensing rules, expert knowledge, and multi-modal data, to provide numerous, diverse, and reliable sensing scenarios for the fine-tuning of foundation models-powered CSI. In this way, we are able to create a controllable, interactive, accessible, and reliable environment for the evolution of foundation models-powered CSI, and greatly help it to depict promising application prospects in real sensing scenarios.

C. Human-oriented operating systems: the integration of intelligence

The strong and reliable machine intelligence powered by foundation models and scenarios engineering promotes the realization of CSI to take a big step forward. Nevertheless, human intelligence is also important for CSI, as it boasts exceptional abilities in learning, reasoning, social interaction, and

cognition [42]. To fuse human intelligence and machine intelligence for building a complete CSI, the machine intelligence needs to be integrated within the human-oriented operating systems (HOOS) to provide services for different kinds of users, facilitate efficient communication among participants, and build the sustainable ecology for smart operations [19].

Specifically, machine intelligence such as ChatGPT and other foundation models is expected to serve as the model base of HOOS. Benefiting from the powerful computing and storage capabilities, all kinds of data, knowledge, algorithms, and resources can be well organized. By decoupling the business logic from the underlying complex intelligent technologies, the HOOS can provide a direct, easy, and user-friendly interface for both participants and developers. To achieve better human-machine interaction, the interface should be designed with in-depth consideration of the load, personality, behaviors, and habits of users. Besides, it also needs to be agile to adapt to different users and tasks by adjusting its functionality and interface.

The success of ChatGPT presents us with a promising form of general HOOS as an intelligent conversational system. In the future, the communication of the digital and biological participants may be all carried out with conversation. The conversational system allows digital participants to interact with biological participants in a human-like way, reducing the learning curve and making the interaction more intuitive and the operation smarter [19]. Compared with visual or touch-based mode, conversational communication usually brings less intervention to what users are doing, which is sometimes important in the scenarios of ITS, such as the driving scenarios.

IV. THREE STAGES OF CSI

To interpret the “Generalized Godel Theorem” from the perspective of intelligence, machine intelligence is divided into three levels: Algorithmic Intelligence (AI), Linguistic Intelligence (LI), and Imaginative Intelligence (II) [20]. The success of AlphaGo in 2016 was a milestone in algorithmic intelligence with algorithms for deep, generative, and reinforcement learning [43]. Now, a new milestone for linguistic intelligence has been erected with the emergence of ChatGPT [20]. With the massive absorption of human linguistic information and vast parameter scale, linguistic intelligence can achieve a highly human-like conversational experience. The achievement of algorithmic intelligence and linguistic intelligence leads us to ponder what form will the next milestone of imaginative intelligence take, and how are the three stages of intelligence represented in CSI.

A. Algorithmic intelligence

Most of the current research on CSI can be categorized into algorithmic intelligence, in which an overall framework is established firstly to divide the complex sensing process, then, specific algorithms or models are designed for solving sub-problems [44]. Under pre-defined frameworks and algorithms, algorithmic intelligence can perform the rigorous computation to meet human requirements and optimize metrics of interest, such as coverage [45], cost [46], and efficiency [44]. It can be

seen that algorithmic intelligence has freed humans from the heavy computing burden, but humans still need to think about the design of sensing schemes and express them in a form that algorithmic intelligence can understand (e.g., code).

B. Linguistic intelligence

Powered by advanced foundation models, especially the Large Language Models (LLMs) such as ChatGPT, linguistic intelligence offers machines communication channels to humans in a conversational manner and the ability to understand the complex and abstract needs of humans [27]. It enables the effective transmission between human requirements, thoughts, and concepts with algorithmic intelligence, and language could be a generic interface to empower this. Now, linguistic intelligence has already implemented some concrete applications. Cui et al. [47] proposed a framework called Language-Informed Latent Actions with Corrections (LILAC) to allow users to provide online natural language corrections to the robot at any point during the movement. Shen et al. [48] proposed HuggingGPT, a framework that leverages LLMs to connect various algorithmic intelligence models to help people to solve complicated tasks with different domains and modalities. Inspired by these studies, we can give the basic form of CSI in the linguistic intelligence stage. The sensing participants can talk about their solutions to linguistic intelligence, then, linguistic intelligence can translate the verbal solution into feasible schemes that algorithmic intelligence can handle. Through multiple rounds of communication, linguistic intelligence will provide increasingly explicit and detailed guidance to the schemes and more reasonable organization of sensing resources, forming clear and reasonable control over the sensing process. It can be seen that, beyond algorithmic intelligence, linguistic intelligence can free humans from the heavy burden of expressing, enabling human intelligence to focus on creative and imaginative work, which is conducive to the development of personalized and customized solutions.

C. Imaginative intelligence

As the highest stage of intelligence, imaginative intelligence does not have a prototype yet, but we can still gain its prospect according to the development of algorithmic intelligence and linguistic intelligence. Imaginative intelligence has the potential to further free humans from the heavy burden of thinking. For instance, the sensing participants only need to provide their sketchy ideas or requirements to imaginative intelligence without thinking about the solution, then, imaginative intelligence can understand abstract human intentions and imagine how to satisfy human needs. Finally, the solutions are generated and executed automatically, even though they may not have existed before. To achieve this effect, imaginative intelligence still has a long way to go. Imaginative intelligence needs to be able to generate new concepts and solutions, which not only requires it to be proficient in the underlying business logic but also to be fully aware of the context and the people it is facing. Imaginative intelligence will be a kind of general intelligence, containing and managing more knowledge, with greater capabilities of problem-solving. More

importantly, imaginative intelligence will enter the domain that is unique to human intelligence, i.e., imagination and creation. We believe that the interaction between imaginative intelligence and human intelligence will also take on a more advanced mode than language.

V. CONCLUSION

In this letter, we present the discussion results of the second DHW-CSI, including the participants, methods, and stages of Crowd Sensing Intelligence. With the collaboration of three kinds of participants and the development of foundation models, scenarios engineering, as well as human-oriented operating systems, Crowd Sensing Intelligence continues to accumulate experience during the current linguistic intelligence stage and would achieve a breakthrough to the imaginative intelligence stage at a certain point in the future. We will continue DHW-CSI in the near future. Welcome to participate in future events on Crowd Sensing Intelligence, and any suggestions or proposals are greatly appreciated.

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