Cyber-Physical-Social Systems for Smart City: An Implementation Based on Intelligent Loop

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Abstract: Cyber-Physical-Social Systems (CPSS) provides a novel perspective for constructing “Smart City”, which is also known as the Human-Machine-Things-System (HMTS), focusing on the fusion of ternary space: social network of human society, network of machines and the Internet of things. In this paper, we propose a specific implementation framework of CPSS for Smart City based on intelligent loops, including basic modeling and interactive fusion, state perception and cognition, and adaptive learning. On this basis, an overall architecture of the CPSS platform is designed, which is applied in the urban transportation management in Hangzhou. The application results demonstrate that the intelligent loop could optimize the control and management strategies for actual urban transportation.

Keywords: CPSS, Intelligent Loop, Human-Cyber-Physical Ternary Space

1. INTRODUCTION

In recent years, the rise of Internet and social media has fundamentally changed the management, control, and operation modes of modern engineering and social systems. The integration of engineering complexity and social complexity induced various Cyber-Physical-Social Systems (CPSS) with uncertain, diverse and complex features [Wang, F. Y. 2010]. Thus, how to achieve the integration of human, machine, and things has become one of the hotspots.

Up to now, many well-known scholars and research institutions have explored this issue and outlined the overall roadmap. In 2009, the Chinese Academy of Sciences concluded that Human-Machine-Things ternary computing is the general trend of information technology [Chinese Academy of Sciences. 2009], and made a special research report on “Information Technology: Accelerating the Trinity Fusion of Human-Machine-Things in 2013, where related concepts include Internet of Everything (IoE), Seamless Intelligence (SI) [Alkhatib, H. S., et al. 2015], Cyber-Physics System (CPS) [Rajkumar R., et al. 2010], Inclusive Calculation [Fang, J., et al. 2013]. Academician Y. H. Pan proposed the core concept and development suggestions of Artificial Intelligence 2.0[Pan, Y. 2016], explaining that the world is moving from the original binary space–including social space and physical space to the new ternary space. G. J. Li believed that the most leading new technology to promote economy is the intelligent technology of CPSS in 2017 [Li, G., Xu, Z. 2017]. In the same year, the Journal of Information and Electronic Engineering of the Chinese Academy (English), described in depth the Big Data Intelligence, Group Intelligence, Cross-media Intelligence, Hybrid-enhanced Intelligence [Pan Y. 2017][Zhuang, Y. T., et al. 2017][Zheng, N. N., et al. 2017]. In terms of application, CPSS is applied mainly to the collaborative management in Smart City’s transportation system. Xiong studied the application of parallel transportation system for subways and bus rapid transit [Dong, X., et al. 2017][Xiong, G., et al. 2017]. He et al. utilized social signals to issue guidance information such as shortest and fastest traffic path for travellers [He, K. 2016]. Ye et al. presented the modelling method of urban population synthesis and its application in population calculation and emergency evacuation [Ye, P., et al. 2016] [Ye, P., et al. 2018].

Summarizing the research above, current achievements in CPSS mainly focus on two aspects: from the perspective of the overall situation, the top-level design of CPSS is characterized to grasp strategic direction but lack of specific implementation; from the perspective of specific technologies and applications, intelligent information system for local area can be developed, characterized by one-sided attention to a single field and lack of integration means. In all, It seems to be still lacking a unified framework in terms of model, algorithm and other software levels, to achieve the integration of specific applications. In summary, this paper has the following contributions:

•We propose a CPSS framework based on intelligent loop for the fusion of three spaces, and analyse problems of basic model and fusion, perception and cognition, and learning.

•We further design a CPSS cloud platform, and example urban transportation to demonstrate the whole integration process.

• Empirically, we demonstrate the effectiveness of our proposed T-CPSS model based on intelligent loop.

2. BASIC MODELING AND FUSION METHOD IN HUMAN-CYBER-PHYSICAL SPACE

Social space for human studied in this paper refers to the participants of various activities in the city. Physical space for things includes infrastructures, such as vehicles, traffic signals, etc. in traffic. Cyber space for machines refers to the information system connecting the human and physical space, including communication channels, algorithms, software.

2.1 Urban population modelling for human based on Multi-Agent in social space

For the modelling of social space, multi-agent method is proposed, which can be divided into two steps: static population synthesis and dynamic model calibration (Fig.1).

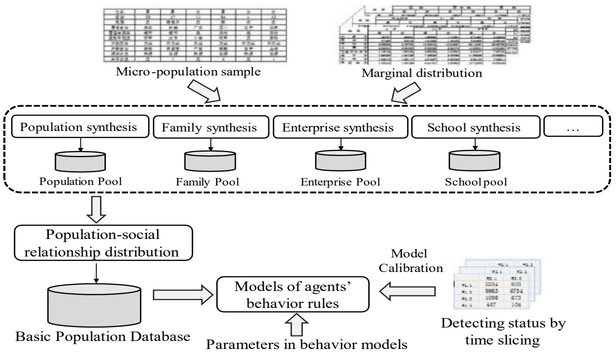


Fig. 1. Framework of urban population model

Static population synthesis, takes multi-source data such as census, statistical yearbook as input, is to generate a basic population database containing various social relationships such as families, enterprises, and schools. Firstly, based on original input data, we obtain the micro-population sample and the marginal distribution. Then use Bayesian network [Sun L., Erath, A. 2015] and JDI (Joint Distribution Inference) [Ye, P., et al. 2017] to synthesize the joint distribution containing all attribute variables. Next, individual population and various social entity pools are exacted by Monte Carlo simulation. Finally, based on the population-social relationship allocation algorithm [Ye, P., et al. 2020], individual records and social entity records are associated according to the composition relationship, and a static population database containing all-round social relationships is obtained.

The second step is the establishment and calibration of agent's dynamic behavior model. This aims to build a full-process perception-cognition-decision model, involving explicit and inexplicit human behavior rules such as travel motivation, attention, planning, and actions. After the behavior rules are determined, the calibration of the rule parameters determines, which is the key to ensure that the evolution of the population system can truly reflect on the operating rules of the actual system. Let the state transition equation of the agent be

$$\mathbf{N}(k+1) = \mathbf{T} \cdot \mathbf{N}(k) \quad (1)$$

And observation equation of the system:

$$\widehat{\mathbf{N}}(k+1) = \mathbf{W} \cdot \mathbf{N}(k+1) \quad (2)$$

Where $\mathbf{N}(k)$ denotes the state vector of agents in different states in step k; $\mathbf{T}$ denotes state transition matrix to be solved; $\widehat{\mathbf{N}}(k+1)$ denotes the observation vector observed by the actual system, $\mathbf{W}$ denotes the observation matrix. With recurrence of calculation, the number of available equations increases, which eventually converts to an optimization problem of higher-order Markov chain:

$$\mathbf{T}^* = arg\min_{\mathbf{T}} \sum_{l=1}^{n} \gamma_l \left\| \widehat{\mathbf{N}}(k+l) - \boldsymbol{W} \cdot \mathbf{T}^l \cdot \mathbf{N}(k) \right\|_2, k = 1,2, \ldots \quad (3)$$

n is the order of error considered, $\gamma_l \in (0,1)$ is the discount factor for each step. Except for the state transition matrix to be sought, the rest are all known. Therefore, each summation term can be regarded as an equation group with $|\mathbf{T}|$ unknown numbers and $\left|\widehat{\mathbf{N}}(k+l)\right|$ equations. The number of equations increases with n increases, and $\mathbf{T}^*$ can be obtained with assistance of ample observation data. Finally, calibration can be completed by reversing parameters of the agent behavior model based on the state transition rule under $\mathbf{T}^*$.

2.2 Basic resources modelling for things based on Knowledge Graphs in physical space

The modelling of urban basic resources is established in the form of Knowledge Graph, which expresses the relationship between different objects in the form of triple: <Subject, Predicate, Object>. We abstract each pair relationship of the Subject and Object as nodes, and the Predicate as connected sides. The Knowledge Graph can be transformed from existing datasets, or can be constructed by semi-automatic or fully automatic Data Mining methods. Here we take the semi-automatic method as an example. Firstly, the original knowledge data are obtained and structured based on open source databases and network query APIs, and then the attribute concept is extracted from the structured datasets. Finally, make semantic matching to generate the relationship between data and attributes. The calculation method of the attribute relationship is to use the text similarity comparison in information retrieval, that is

$$Simi = \frac{\sum_{a,b}|\{e|e(A)=a,e(B)=b\}|}{\sqrt{\sum_a|\{e|e(A)=a\}|}\cdot\sqrt{\sum_b|\{e|e(B)=b\}|}} \quad (4)$$

Where a, b are corresponding specific values of attribute A, B, $|\{e| *\}|$ are the number of instances meeting condition$*$. In the case of multiple data sources, each source can generate a small Knowledge Graph. The fusion of Knowledge Graph is mainly accomplished through the unification of conceptual terms and pattern link point matching. This process generally uses semantic matching to link data entities and known knowledge under manual guidance, the association fusion will be realized by the matching of pattern link point.

2.3 *Information system modelling for machines based on Edge Computing in cyber space*

We propose Edge Computing (EC) to divide the center-edge two layers to implement information system model (Fig.2).

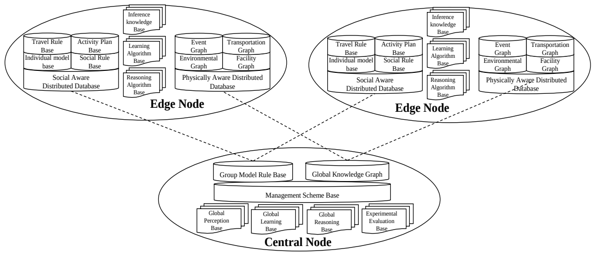


Fig. 2. Information system modelling scheme in cyber space

Edge nodes are oriented to local application scenarios, completing simple perception. Its composition includes three parts: data, model knowledge and intelligent algorithm. Data component relies on a distributed database to store physical and social perception data in local scenes. Model knowledge component stores descriptive knowledge of human and things. Intelligent algorithm component includes perceptual algorithm database, learning algorithm database and knowledge reasoning database: the former is used to format, extract and correlate the perception results of multiple data sources; the middle is used to incrementally learn and calibrate the basic model of human and physical objects more completely; the latter is used to generate the optimal service and management plan, and send instructions to basic resources to deliver guidance information.

The central computing node is oriented to urban-level scenarios, and completes the overall regional collaborative optimization. Similar to edge nodes, the central node contains two parts: global model knowledge and intelligent algorithm. Global model knowledge part records the behavior rules of groups and Knowledge Graphs of urban resources more generally. The management plan database is used to store typical urban management strategies in different conditions. Intelligent algorithm part includes global perception, global learning, and global reasoning. The evaluation algorithm library is used to conduct computational experiments.

2.4 *Interactive fusion of Intelligent Loop in CPSS*

The fusion of ternary space involves intelligent loop on two levels—edge-level local intelligent loop and urban-level global intelligent loop (see Fig.3), which aims to clarify the logic relationship of the ternary space in the interactive fusion from the perspective of information flow, and study the entire process of information processing.

First, EC is to form an edge-level local intelligent loop, which is used to solve the local optimal control at a lower level. Second, the modelling of the cyber space is improved through the fusion and evolution of human modelling and Knowledge Graph. Third, for large-scale and city-level coordination and optimization, demarcate dynamically the parameters and real-time state of the behavior model in artificial system through perception in social and physical space, and carry out reliable CPSS fusion experiments in cyber system to deduce the dynamic evolution rules and characteristics of the system. Finally, complete the construction of the Smart City's global intelligent loop by determining the optimized management plan, and completing the precise management of the actual infrastructure and the visual guidance of the social population.

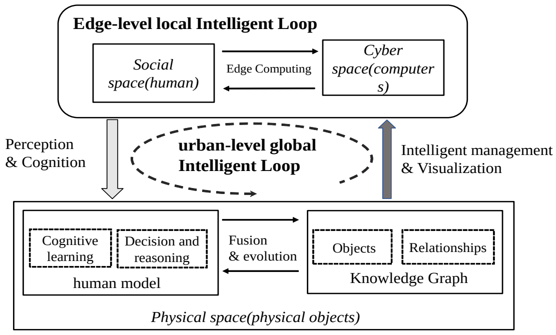


Fig. 3. Fusion of Intelligent Loop in ternary space

3. PERCEPTION OF INTELLIGENT LOOP

Perception and cognition can be regarded as the dynamic evolution of CPSS in time dimension. The Edge-Cloud Fusion is used to study the cognitive theory of intelligent loop in Smart City CPSS. Similarly, we propose the cognitive theory of CPSS on two levels: (1) on the level of local scenes: to study the edge-level intelligent loop of the social and physical space.(2) on the overall macro level of the city: to study the urban-level complex intelligent loop(Fig.4).

3.1 *Local scene perception based on region division and time slicing*

For the edge-level Intelligent Loop, we propose division of spatial-physical areas and time slicing, to realize the scene description in specific time of local areas. First, in the geographical space, the fine-grained division of urban areas will be carried out considering the EC platforms as the logical center. Within local region, the fusion, filtering, and storage of heterogeneous multi-source data in CPSS is completed. Then data are sliced in time dimension. The EC platform can dynamically adjust the time slice interval according to different demands, data in which is the abstract description in the local area within the time interval. Finally, data in local scene is visualized and described digitally, including the specific geographic location, time and occurrence of events.

Reinforcement Learning (RL) is designed and adopted for local perception and cognitive requirements, where agent adjusts its strategy through interaction with environment. Suppose S_t denotes environment state at time t. The EC platform selects an action A_t with a reward $R_{t+1} \in R \subset \mathbb{R}$ at time $t+1$. When given state s and reward r at time $t-1$, the probability of transforming to state s' and obtaining reward r at time is t can be expressed as

$$p(s',r|s,a) \triangleq Pr\{S_t = s', R_t = r | S_{t-1} = s, A_{t-1} = a\} \quad (5)$$

The state transition probability is:

$$p(s'|s,a) \triangleq Pr\{S_t = s' | S_{t-1} = s, A_{t-1} = a\}$$
$$= \sum_{r\in\Re} p(s',r|s,a) \quad (6)$$

The expected rewards for state-action pair is:

$$r(s,a) \triangleq E[R_t | S_{t-1} = s, A_{t-1} = a]$$
$$= \sum_{r\in\Re} r \sum_{s'\in S} p(s',r|s,a) \quad (7)$$

The expected value of the next state tuple is:

$$r(s,a,s') = \sum_{r\in\Re} r \frac{p(s',r|s,a)}{p(s'|s,a)} \quad (8)$$

3.2 Urban global scene intelligent perception based on the extension of multi-source local scene perception

After forming the edge-level intelligent loop for perception in Social-Physical space at local scenes, edge nodes periodically send fine-grained scene data to the central cloud platform. The central cloud platform automatically generates aggregation results through configurable modes. For example, suppose that edge nodes send the number of vehicles passing through each intersection in the urban transportation scene every 5 minutes to the central cloud platform. Based on this, the platform can calculate indicators, such as the average number of vehicles, the total number, etc. in this scene at different time granularities such as every hour, every day, and every week.

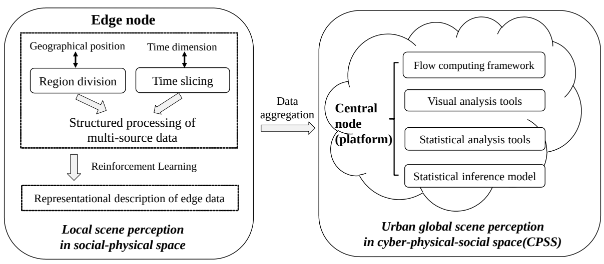


Fig.4. The perception framework based on Intelligent Loop

In order to obtain a portrait description of a multi-edge scene, a calculation mode and frame for edge information analysis can be designed. First of all, using distributed Big Data computing tools, through the stream computing architecture model, integrate sources of scene information in different regions of the city. Secondly, based on various of visual analysis tools(spatio-temporal matrix, and multi-colour mode assisted cognition, etc..), as well as multiple statistical analysis tools(data dimensionality reduction, optimal linear sorting, etc..) we achieve a broader and deeper scene description of the whole city. Finally, comprehensive statistical inference models such as Bayesian networks are proposed to provide comprehensive information on the entire city in different dimensions such as time, space, and various applications.

4. THE COLLABORATIVE LEARNING OF INTELLIGENT LOOP

The learning of intelligent loop is to realize collaborative learning by means of visualization and other enhancement measurements. The closed-loop can be regarded as two independent and interactive subsystems: the actual system—formed by social space and physical space; and the artificial system—formed by social space and cyber space. In the whole urban-level intelligent loop, we propose the following modes: (1) From physical space to cyber space, the knowledge automation of man-machine hybrid is studied: by means of data and calculation, the optimization modelling of "artificial system" from physical space is constructed automatically; (2) From cyber space to physical space, Human-Cyber cooperative learning of intelligent loop is studied: the simulation, verification and evaluation results of cyber space is used to verify and execute in the "actual system"; (3) Continuous iterative optimization to form a synchronous mapping mechanism of CPSS (Fig.5). In this mode, we consider "human" as an enhanced force, that participates in the understanding and perception of data, intervenes the optimization and evaluation of the intervention model.

4.1 Knowledge learning from physical space to cyber space

The operation mechanism from the actual system to the artificial system can be enhanced by three aspects (Fig.5). Firstly, original data can be collected from the actual city and used to conduct visual analysis(scatter map, etc..), in order to obtain the distribution features and visual representation of data and guide the dynamic calibration of multi-agent artificial population model. Secondly, build cognitive model and complete visual analysis. Through combining the semantic cognitive quantitative model of multi-dimensional spatiotemporal heterogeneous data, especially the visual data mining method and the visual parameter adjustment mechanism based on the Bayesian network, the understanding of the internal details of this model can be enhanced, which benefits better diagnosis and adjustments of the model parameters. Thirdly, through visual analysis of the scheme model based on Bayesian network expression, different schemes can be presented and evaluated more intuitively. And with the help of comparisons of statistical parameters, the temporal and spatial distribution and comparison of visual feature elements containing statistical data in urban air can be designed, and the optimal model can be obtained.

4.2 Knowledge learning from cyber space to physical space

Firstly, based on the original experimental data in the artificial system and perception data in the actual system, visual analysis and feature extraction are completed to verify the effectiveness of the artificial population model. Secondly, through visual analysis of various assumptions and possible Smart City management schemes in experimental verification, a distributed fast approximate calculation method based on microservice architecture is designed, which is convenient for real-time adjustment of model parameters, enhancement of internal understanding of calculation experiment results.

Thirdly, the results of large-scale calculation experiments are evaluated comprehensively and quantitatively. The optimal Smart City management scheme is selected to guide the actual system dynamically. Furthermore, the artificial system tends to the actual system through computational experiments. Finally, the above processes are implemented in parallel to achieve the dynamic management application requirements of Smart City, especially in the field of transportation.

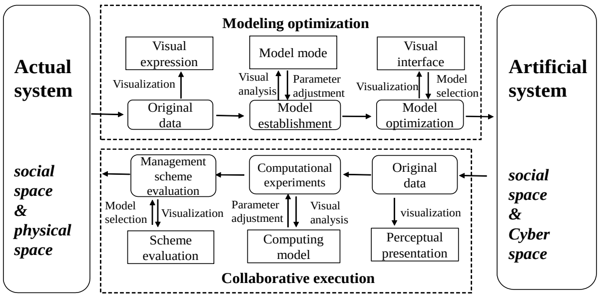


Fig.5. The learning framework of Smart City

5. CASE STUDY: REALIZATION OF T-CPSS

Based on the achievements of the basic model of human-machine space, intelligent loop architecture, intelligent loop cognitive theory, intelligent loop learning method and so on, we take Hangzhou transportation CPSS as an example to show the whole process of the construction of urban intelligent transportation loop system, and verify the effectiveness of CPSS based on intelligent loop framework.

5.1 Construction of urban T-CPSS based on Intelligent Loop

Intelligent loop for urban transportation CPSS is mainly composed of urban-level traffic management cloud platform (cyber space), and human and physical space connected by edge-level intelligent loop. The cloud platform has three layers (Fig.6). In the data layer, basic model of three spaces will be distinguished, and perception data from social and physical spaces will be stored. In the knowledge layer, models in social space are realized: the individual travel rules, activity plans, social interactions, etc., and the Knowledge Graphs of physical space are constructed: transportation infrastructure knowledge map, traffic status knowledge map, etc.. Based on the data from social networks, mobile signals, video monitoring, and so on, we complete the model calibration of multi-scale network social groups and the iterative updating of knowledge system. In the fusion experiment layer, we establish intelligent city management scheme database, scene generator, model loader, loop cognitive learning and other modules, dynamically configure individual behaviour model and knowledge category, complete the integration experiment and carry out visual evaluation of various management strategies. Finally, the optimized management strategy will be delivered to and guide the actual system.

The edge-level intelligent loop is mainly composed of the intelligent learning module, scene recognition module and scene generation module of the edge node. The current local scene can be obtained using perception data from social space and physical space through intelligent learning and cognition, and then optimize the delivered management strategy. The inferred time-sharing scene data will be generated in the form of scene slices and saved in the scene generation module. Edge nodes also communicate with the cloud platform, so as to achieve local data reporting and city portrait drawing.

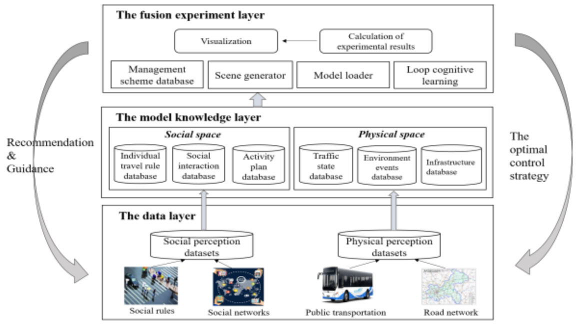


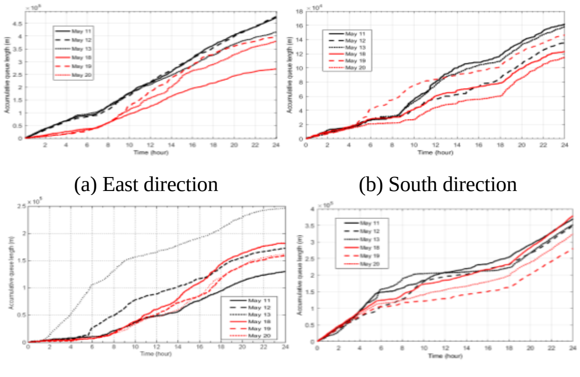
Fig.6. Framework of Intelligent Transportation platform

5.2 Experimental verification of urban T-CPSS

Relying on the transportation CPSS based on intelligent loop, we take Hangzhou City (in Zhejiang Province) as the target city to verify feasibility and effectiveness of CPSS based on intelligent loop. First, according to the typical scenes of individuals and families, such as going to school, the internal edge-level intelligent loop of each scene is completed and guides the local intelligent control. Then, utilizing analysis of the social traffic behaviors when completing the activity plans, the urban-level transportation intelligent loop is deployed by connecting each edge-level scene loop in series. Finally, the urban-level intelligent loop for T-CPSS is established. The cloud platform will realize the optimal management plan of the actual system, to guide the collaborative optimization.

Fig.7. Experimental area of T-CPSS in Hangzhou

Our experimental area includes 3 intersections in Hangzhou surrounded by Wenyi Road, Moganshan Road, and Jiaogong Road (Fig.7). Take the intersection of Wenyi Road and Moganshan Road as an example, through the optimal control of traffic signal using urban intelligent loop system, queue lengths in four directions, which is the cumulative queue lengths along each incoming lane of one intersection[T, Chu., J, et al. 2020], improved obviously. The optimization plan was conducted on May 11, 2020, and Fig.8 demonstrates the comparison of queue length before the implementation of the optimization scheme (May 11-13, 2020) and after the implementation (May 18-20, 2020. It should be noted that May 11 and May 18 have similar traffic demand for the same weekday. For east direction, the queue lengths are decreased by 44.7%, 16.8% and 8.7% in May 18-20 (the whole day), compared with them in May 18-20 correspondingly, verifying the power of traffic signal optimization of T-CPSS based on intelligent loop.



(a) East direction (b) South direction

(c) West direction (d) North direction

Fig.8. Comparison of queuing length before and after the implementation of optimization scheme

In addition, the accuracy of the release on traffic conditions in Hangzhou based on intelligent transportation cloud platform has reached 90%, improving 20% higher than that before the adoption of the cloud platform. And it can release not only the congestion state, but also the travel time of the covered area, as well as traffic control, accident, event and other information, which is more comprehensive and practical than the content released by the state-of-art system.

6. CONCLUSIONS

There are now many achievements in the integration of CPSS, but often plan the integration direction from a macro perspective, lacking specific implementation details; or only focus on the information integration in a certain field, lacking universality. Therefore, it is necessary to design the overall architecture of the integrated Smart City system and introduce intelligent circuits to solve the problems of perception, cognition, learning and circuit fusion in the ternary space.

In this paper, we proposed a novel CPSS framework based on intelligent loop, and analysed problems of basic modelling and fusion, perception and cognition, and learning. We realized the perception of physical objects in Smart City through IoT, and the perception of human through social sensor network technology. Further, we designed a CPSS cloud platform, and took urban transportation as an instance to demonstrate the whole process of integration in CPSS and the power of intelligent loop.

ACKNOWLEDGEMENTS

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