Recent Progress on the Convergence of the Internet of Things and Artificial Intelligence

Feifei Shi, Huansheng Ning, Wei Huangfu, Fan Zhang, Dawei Wei, Tao Hong, and Mahmoud Daneshmand

Abstract

The overwhelming increase of ubiquitous data, connections, and services brings serious challenges, in particular facing the demanding requirements of the Internet of Things (IoT). In order to seek better solutions and achieve more efficient information retrieval, artificial intelligence (AI) serves as a strong technical earthquake and contributes a lot to data analysis and decision making. It plays a compelling role in prompting digital and intelligent services. In this article, we focus on and emphasize the great significance pertaining to the convergence of IoT and AI. We first elaborate two typical forms of AI, namely knowledge-enabled AI and data-driven AI, with a comparison between respective advantages and disadvantages. Then we survey recent progress relating to the convergence of AI throughout the IoT architecture, from the sensing layer through the network layer to the application layer. In addition, a case study of a smart city is presented illustrating the convergence between IoT and AI. Furthermore, we point out open issues worth further research. The convergence of IoT and AI marries the merits of both and enables strong capability of resolving a broad range of problems.

Introduction

The last years have witnessed the huge developments brought by the Internet of Things (IoT). As predicted by the International Data Corporation (IDC), by 2025 there will be 41.6 billion IoT devices or "things" connected together, with generation of 79.4 ZB of data. The great explosion in data, connections, as well as services challenges infrastructures with tremendous volumes it needs to handle, in particular facing the extremely limited resources and highly demanding requirements. Undoubtedly, IoT is truly transforming daily life and industrial manufacturing to new heights of innovation and productivity. It depicts a large network where users, devices, and objects are all connected for data sharing and interaction, which brings a plethora of benefits as well as a whole slew of problems and challenges.

Artificial intelligence (AI) serves as a technical earthquake at the right time, providing humans with augmented welfare and well being, and it has been demonstrated that AI does have strong capability in different aspects like face recognition, credit scoring, decision making, and autonomous driving [1]. The concept of AI originated in the 1950s, and it allows machines to simulate and perform human tasks. With AI maturing at an exponential rate, it enables data to be processed quickly and turned into meaningful decisions with machine learning and neural networks and so on.

In this article, we focus on recent progress brought by the convergence of IoT and AI, which paves a new way for high efficiency in dealing with serious issues and challenges. The convergence means merging or combining distinct technologies, industries, and devices into a unified whole, and here, we initially concentrate on the convergence tendency of IoT and AI, which could be a groundbreaking and instructive study for further research. Generally speaking, AI adds value to original IoT via advanced algorithms (they contribute a lot in mining hidden information etc.), while IoT provides AI with real scenarios and applications. There is no doubt that AI brings greater efficiency and flexibility as well as more innovative intelligence throughout the IoT architecture, ranging from the sensing layer to the application layer. In this article, we first introduce two types of typical AI: knowledge-enabled AI and data-driven AI. Following that, we give a comprehensive overview of the convergence between AI and IoT from the perspective of the sensing layer, network layer, and application layer, including representative techniques and general schemes. In addition, we take cross-platform applications in smart cities as an example to demonstrate the great significance. The aim of this article is to provide a general survey based on the convergence of IoT and AI, and point out the research directions in the future that have the most potential.

The remainder of this article is arranged as follows. The next section presents two types of typical AI and provides theoretical support for later study. Following that, a detailed convergence of IoT and AI is illustrated from the traditional three layers of IoT architecture. And in order to demonstrate the great importance of the convergence between IoT and AI, we take a case study with cross-platform applications in smart cities. Finally, we analyze potential issues worth further research and give conclusions in the last section.

Knowledge-Enabled AI and Data-Driven AI

AI serves as one of the main driving forces in both daily life and industrial manufacturing, and has been gaining ground in recent years. It provides

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Types	Basis	Advantages	Disadvantages
Knowledge-enabled AI	Prior knowledge and rules	Strong rational logic Valuable perceptual cognition Powerful pertinence on specified areas	Uninterpretability Low robustness dealing with infinite complexity Difficulties in describing, formulating, and managing rules Largely influenced by knowledge inventors Costly in refining rules
Data-driven AI	Datasets	Much more objective Little human intervention Crucial reasoning mechanism	Data incompleteness Data inaccuracy Costly in labeling data

TABLE 1. The comparison between data-driven AI and knowledge-enabled AI.

impressive performance in both economic returns and social benefits, and is prompting development of smart homes, smart cities, intelligent transport, smart manufacturing, and more. As generally acknowledged, AI has two main branches during its development, traditional or symbolic AI, which refers to methods based on representations like rules and knowledge, and statistical AI driven by data primarily benefiting from deep learning and neural networks. Many scholars, experts, and engineers in industry and academia have been doing relevant research for a long time, and some even work from the perspective of data-based or knowledge-based. Therefore, on the basis of the existing literature, we classify knowledge-enabled AI and data-driven AI as representative types in our article, and discuss their respective advantages and disadvantages.

The first type of AI is so-called knowledge-enabled AI, mainly depending on transcendental knowledge and rules. The representative features of knowledge-enabled AI are that most models are symbolic and require storing predefined rules, which are the only references for further information processing. Undoubtedly, knowledge-enabled AI achieves periodic progress, in particular in the theoretical research. Afterward, with the boom of expert systems, rational and complete knowledge bases are introduced with better performance. It is a remarkable milestone in the history of transforming AI to practice. Leading companies like IBM have also joined the technical wave, and many representative works like Deep Blue appear. Nevertheless, the fatal limitation of knowledge-enabled AI is that it totally relies on predefined knowledge, which is difficult and costly to be extended with low adaptability.

Another type of AI is data-driven AI, which has flourished with the continuous rise of machine learning and neural networks. This is a stage where machines can automatically learn features and mine knowledge from massive data with little human intervention. It fundamentally reverses the drawbacks of depending too much on predefined knowledge and enables better performance. In particular, along with the prosperous boom of big data as well as the increasing improvement of storing and processing ability, data-driven AI brings an emerging scientific and technical revolution. Alpha Go is a representative product in the era of data-driven AI, with the ability of learning and optimizing chess playing from nearly 30,000 chess manuals and 30 million self-games. However, data-driven AI also encounters limitations. For example, most of the surrounding data are incomplete and fragmented, which increases the difficulty of information processing and analysis. Also, the data distribution status is rarely the same, suggesting lower reusability between different domains.

In general, both knowledge-enabled and data-driven AI have their own advantages and disadvantages. We give a clear comparison in Table 1 in terms of their pluses and minuses. First, knowledge-enabled AI mainly relies on prior knowledge and rules, most of which are abstracted and acquired from experienced experts, as well as acquired valuable common sense. Thus, knowledge-enabled AI usually has strong pertinence on specic problems. However, it shows severe limitations with low robustness when facing complicated and changeable problems. In addition, there are enormous difficulties in describing, formulating, and managing large numbers of rules. And the cost in both time and labor are high for the authority and credibility of rules and knowledge. On the contrary, data-driven AI depends on data instead of prior knowledge and learns features from large datasets with little human intervention. With the continuous development of machine learning and neural networks, data-driven AI achieves high efficiency in information processing. However, the inherent nature of data-driven AI poses high requirements in data quality, while incompleteness and inaccuracy are common challenges facing datasets. Labeling data correctly and rapidly also consumes a lot in both time and energy.

Considering the fact that both AI types have their respective advantages and disadvantages, researchers have begun to explore innovative ideas for AI development. At the 2018 Global AI and Robotics Conference, the idea of the combination of knowledge-enabled and data-driven AI was proposed. It overcomes existing limitations and paves a new way to exploit cutting edge techniques. By marrying both advantages, the new generation of AI presents huge potential throughout the whole IoT architecture, and stretches out to diverse applications ranging from smart homes and intelligent transport to smart manufacturing, intelligent logistics, and so forth.

An Overview on the Convergence of IoT and AI

The explosive increases in IoT things, objects, and resourcesdo challenge fundamental infrastructures heavily. In order to better deal with the contradictions between high requirements and limited abilities, the convergence of IoT and AI contributes a lot by opening up an unprecedented paradigm, where most IoT data and information can be processed quickly and efficiently. In this section, we analyze the convergence of

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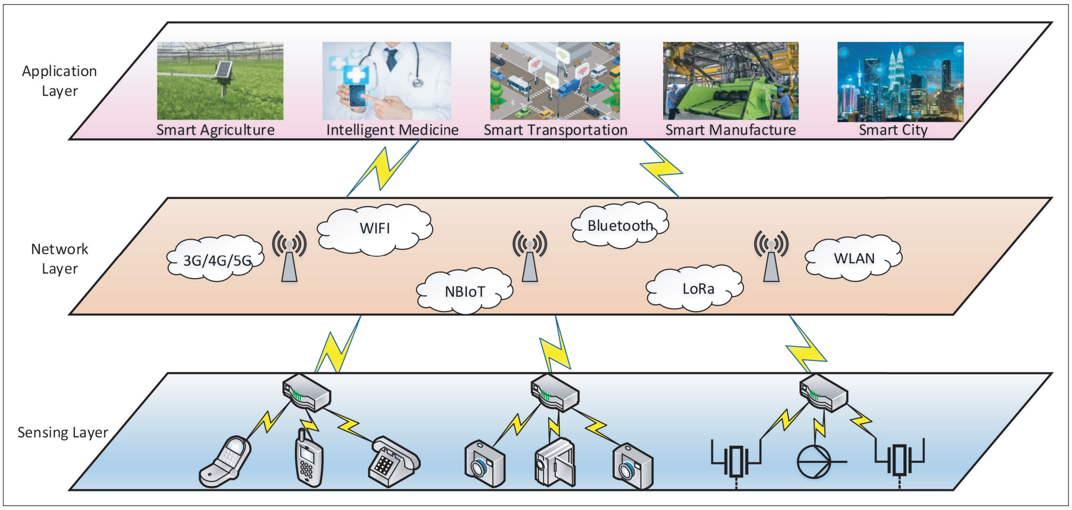

FIGURE 1. The three-layer IoT architecture.

AI throughout the IoT architecture, especially how AI deeply influences and changes IoT in each layer.

In order to provide a more pervasive description, we refer to the most general three-layer IoT architecture, that is sensing layer, network layer, and application layer, shown in Fig. 1. We analyze the convergence of AI and survey relevant AI techniques merging in each layer. Moreover, general converging schemes of AI in each layer are designed and depicted in the direction of data flow, from data access in the sensing layer and transmission through the network layer to processing and analysis in the application layer.

The Convergence of AI in the Sensing Layer

As data is the core foundation of both IoT and AI, it drives substantial opportunities for mining value-added services. However, the astonishing growth in data volume, types, and dimensions along with the high demands on sensing and computing capacity are very challenging. In addition, explosive data often appear suddenly, accompanied by uncertainty and complexity, and it causes traditional IoT algorithms to fail to acquire and process large amount of data instantly. AI appears at the right time, and the convergence of AI in the sensing layer achieves technical breakthroughs in dealing with explosive data.

In order to achieve the balance between incremental data explosion and limited sensing resources, selective sensing is proposed inspired by biology and neural systems. It means to focus on information appealing to the observers most, and in sensing layer, various AI algorithms are defined for improving accuracy and efficiency of selective sensing. Cretu [2] proposes a neural gas network for automatic selection of observable regions with relevant measurements. This architecture starts from a sparse scanning model and is continuously enhanced via data training. It finally achieves significant benefits in time cost when doing 3D sampling and sensing. In order to detect vehicles in aerial images, Tewari [3] also presents a selective search algorithm and designs deep-learning-based classifiers for achieving exemplary performance, with an accuracy of nearly 96 percent in vehicle detection.

The mentioned circumstances mainly rely on data-driven AI where models or algorithms are constantly improved via large dataset training, while there are still circumstances with no available resources or datasets, where knowledge-enabled AI prompts the performance of selective sensing. The top-down attention occurs oriented by prior knowledge or rules, for instance, if users plan to purchase cars, they may pay much more attention on advertisements regarding cars. In 2013, Ning [4] proposed a resource allocation mechanism for sensors in the Web of Things (WoT). It is inspired by human attention and integrated with rules regarding filter or bottleneck, central resource capacity, and multiple resource as guidance. After that, in 2019 he paid attention to an attention-mechanism-inspired selective sensing framework with associated rules and knowledge [5]. Perera [6] designed a context-aware sensing platform (C-MOSDEN) that depends on a selective mechanism on the basis of user-defined queries, and demonstrates great efficiency in real scenarios with processing context-aware selective sensing.

To sum up, AI provides better selective sensing in the sensing layer, with knowledge-enabled AI dealing with resource-restricted cases and data-driven AI for large-scale circumstances. As shown in Fig. 2, we draw a general scheme of the convergence between the sensing layer and AI, and it opens up a new way to achieve selective sensing.

The Convergence of AI in the Network Layer

The data and information then simultaneously enter the network layer during the digitalization era, which brings an excessive burden in network transmission. As communication infrastructure like satellites, towers, and poles are nearly reaching saturation, the limited communication capacity with extraordinary massive connections is facing a serious challenge. Also, it is equally important to achieve efficient communication in the network layer. Song [7] once discussed AI-enabled IoT networks, where deep learning and neural networks were adopted for different network architectures. It is acknowledged that AI helps a lot in selecting the best routing path, optimizing network scheduling, enhancing the

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quality of service (QoS), establishing effective connections, and achieving efficient communication via knowledge-enabled and data-driven methods.

First, selecting the most appropriate routing path is important in improving the communication efficiency of the network layer. For lightweight networks like wireless sensor networks, most prefer to choose a routing path based on predefined rules or knowledge. For example, Guo [8] establishes a functional ontology of routing reputation in mobile ad hoc networks. The reputation ontology provides a trustworthiness calculation of the best propagators that can forward packets in the routing process in case of any selfish routers behaviors. Esmaeeli [9] presents an energy-based clustering protocol in consideration of the energy consumption and proximity of nodes. It refers to the game theory and fuzzy logic, which finally reveals better performance in prolonging the network life compared to others. For heavy networks with strong and complicated devices, popular routing protocols including Open Shortest Path First (OSPF) and Enhanced Interior Gateway Routing Protocol (EIGRF) are mostly adopted. They have predefined parameter metrics, which could enable routers to calculate and select the best routing path automatically.

Optimizing network scheduling is also a significant part of achieving efficient communication. Network scheduling means evaluating the current network quality in order to dynamically generate the most appropriate scheduling plan for the network resources. Therefore, neural networks, machine learning, and reinforcement learning are popular for providing a best network schedule. Due to the limited network and computational resources, [10] proposes a scheduling strategy that combines BP neural network and fuzzy feedback, and it demonstrates better performance with existing running conditions. Another aspect of enhancing communication efficiency is data fusion and compression during transmission, where data-driven AI plays a functional role in improving the communication performance. Wang [11] introduces a selective compressing sensing architecture for implantable neural decoding combined with a deep learning fine-grained analysis, which is aimed at reducing the wireless transmission burden and improving the efficiency. In 2009, Pinto [12] offered a Genetic Machine Learning Algorithm (GMLA) for achieving communication efficiency optimization in wireless sensor networks. The GMLA shows a better trade-off between communication efficiency and QoS. In addition, the QoS during the network communication also counts a lot, which includes the transmission bandwidth, time delay, as well as data packet loss rate. AI algorithms such as fuzzy logic and neural networks have also shown substantial potential for improving the QoS throughout the network.

Based on current research work, we present a general scheme for the convergence of AI in the network layer, shown in Fig. 3. As it is urgent to balance the limited communication resources and demanding connection requirements, exploiting effective ways to achieve efficient communication holds a substantial position. AI contributes a lot in self-organizing path scheduling, connection overhead reduction, as well as other procedures during the communication, in a way that depends on either prior knowledge or enormous generated data. It not only reduces human intervention during the network management, but also enables better performance with higher reliability and adaptability.

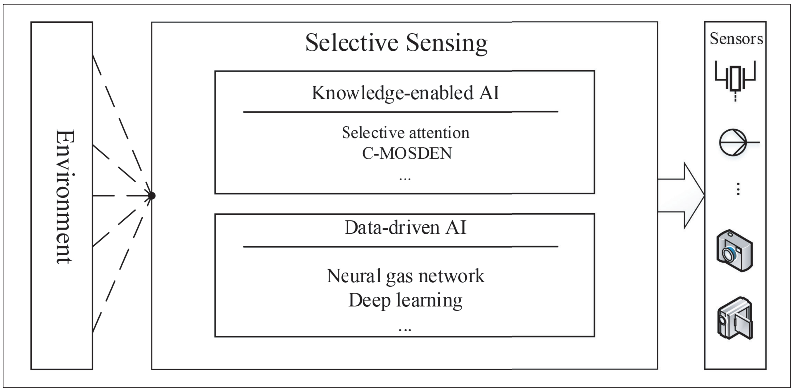

FIGURE 2. The general scheme of the convergence between the sensing layer and AI.

The Convergence of AI in the Application Layer

The application layer provides a vast set of applications that users can access directly, while the explosive growth of applications coupled with diversified and personalized service requirements indeed poses unprecedented challenges. For instance, different users may have various requirements even if they are searching for the same information. Thus, adaptive service, aimed at providing the most appropriate service for specific users, has huge potential in the application layer, where AI contributes a lot in helping understand personalized services and enhance users' satisfaction.

In order to provide adaptive services for different user requirements, user profiles are significant. Ontology modeling is a representative way that helps a lot in better understanding and analyzing different user requirements. The ontology models will be then trained or updated with enormous datasets, which is a kind of data-driven AI. Ning [13] designed a friend recommendation system on the basis of the Big-Five traits model, which can be regarded as an ideal theory established with machine learning, semantic technologies, as well as large-scale data from a personality social network. Eyharabide [14] also offered an initial ontology to describe user profiles; the ontology is enriched through Bayesian networks for learning context-enriched user profiles.

At present, both knowledge-enabled and data-driven AI have been widely utilized in information mining and recommendation systems, and have shown exemplary performance in providing the most appropriate service. It provides huge possibilities for fully capturing and analyzing various user requirements. As depicted in Fig. 4, a general framework of the convergence between the application layer and AI is presented in the case of providing adaptive service for users. When users propose a specified requirement for a given application, AI can help deeply analyze user profiles and learn hidden information with data mining methods. The combination

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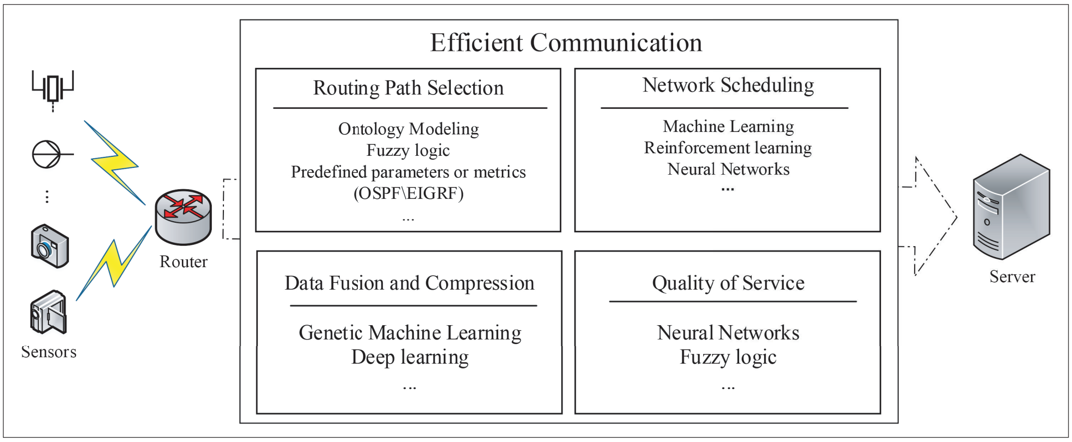

FIGURE 3. The general scheme of the convergence between the network layer and AI.

of both data-driven and knowledge-enabled AI makes full use of respective advantages, and it extensively enables the adaptive service under massive applications and complicated personalization.

Case Study

In order to exemplify the significance of the convergence between IoT and AI, we provide a case study of smart cities as IoT microcosms. Smart cities are equipped with different types of electronic sensors and devices, and aim to provide various value-added services for administrations and citizens. Most countries are starting to construct smart cities with high quality of life and valuable services. In this section, we introduce the convergence of AI in smart cities, particularly in enabling adaptive services.

As shown in Fig. 5, we take cross-platform applications as a representative case scenario in smart cities. It is designed in accordance with the traditional three-layer architecture, with fundamental sensors composing different platforms in the sensing layer, communication devices and servers belonging to the network layer, and high-level services such as transport and parking, garbage collection, and intelligent lighting in the application layer. Considering the restricted storage, transmission, and processing ability of existing infrastructures, as well as the variety and heterogeneity of enormous devices and resources in smart cities, a collaborative open architecture based on end-edge-cloud computing [15] is preferred for achieving selective sensing, efficient communication, and adaptive service. The main aim is to make the greatest use of limited resources and provide the most appropriate service among various and personalized requirements.

The end-edge-cloud computing model needs different edge servers apart from traditional end nodes and cloud servers, which are responsible for sensors and devices in the nearest area. That is substantial for relieving the pressure of upper-level servers as well as the network load during transmission. The collaborative architecture proves to be an efficient way of dealing with massive data and connections in smart cities; meanwhile, it supports high and efficient services by adopting methods like AI and the knowledge graph.

In order to provide adaptive services, a knowledge graph is pre-stored in each server (both edge server and cloud server) serving as the reference for service resolution. The knowledge graph is initially established based on prior knowledge and existing resources, which translates the mapping relationships between low-level resources and high-level applications. When the service requirement comes, the cloud server in the application layer analyzes and assigns the mission to a specified edge server for concrete resolution, where the knowledge graph contributes a lot in helping find the most accurate resources. When new resource or data comes, the knowledge graph will be updated via data-driven AI algorithms like machine learning and neural networks. It would achieve efficient service resolution with the combination of both knowledge-enabled and data-driven AI.

This well-defined architecture strongly supports intelligent cross-platform applications. For example, if the resources mapping with the given service requirement are in a neighboring area, it means there is no useful information in the current knowledge graph for the specified service resolution. Then the responsible server may send requests to the next server for cross-platform resources resolution. Undoubtedly, all new information will be regarded as references for the knowledge graph to update for further resolution.

Although smart cities are also confronted with issues of massive data, heavy network overload, and various service requirements, AI helps a lot in dealing with such challenges. Nowadays, leading companies all over the world are deploying related plans of smart cities, aiming to make the cities better by adopting the latest AI techniques. For example, Alibaba released the ET city brain plan in 2016, and Hangzhou became one of the first cities to have its own brains. The intelligent brain uses real-time and full-scale data to optimize city public resources globally, correct city operational defects instantly, and successfully achieve triple breakthroughs in city governance, service, and industrial development. Compared to the traditional city operational mode, the ET city brain adopts AI in its management, such as the independently developed platform MaxCompute for big data processing, real-time video recognition, and automatic detection, as well

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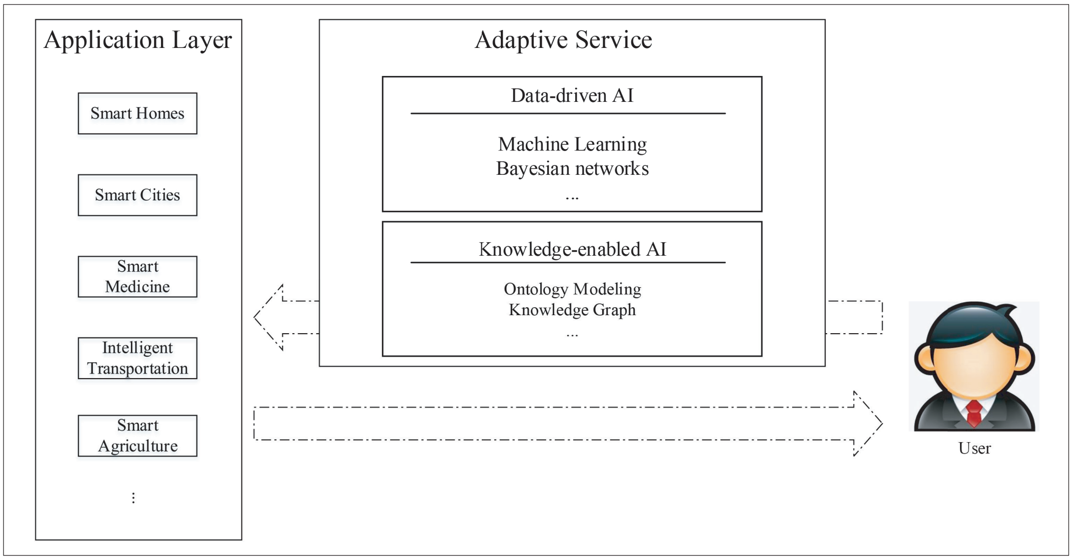

FIGURE 4. The general scheme of the convergence between the application layer and AI.

as the physical architecture of brain-like neural networks. Particularly in the aspect of a traffic system, the ET city brain first applies image recognition techniques to analyze more than 3000 real-time videos. The utilization rate of videos has been enhanced from the original 11 percent (mainly depending on manual detection) to 100 percent, and accuracy for low-resolution vehicle detection is as high as 91 percent. In addition, combined with diversified and multi-modal data like location and road conditions, the city brain achieves high efficiency in real-time traffic analysis, and could optimize and adjust traffic lights in time.

Similarly, Sidewalk labs of Alphabet also presents comprehensive plans related to smart cities. It launched the Sidewalk Toronto project relying on Toronto's eastern waterfront, and aims to shape the future of the city and provide a global mode for inclusive urban development. The idea is to connect smart living, intelligent transportation, public space, and fundamental architecture together through technology and data, so as to equip the city with intelligent brain and advanced limbs as well as sensory systems. Sidewalk Toronto allows the physical layer and the digital layer to merge, where it provides more flexible buildings, people first streets, more inclusive public spaces, and open utilization of underground infrastructures. Therefore, intelligent technical support is inevitably required for such high-level services, such as intelligent traffic lights based on AI and machine vision, intelligent parking toll systems, drones, logistics robots, LED variable lane systems, free high-speed wireless Internet, data standards for city event awareness, machine learning modeling for infrastructure status, deep learning cameras with front-end structured processing capabilities, and so on. With the convergence of AI, everything in Sidewalk Toronto becomes connected and sensible, ranging from smart sensors and devices to fundamental infrastructures. Bicycles could be accessed on demand at very low prices benefiting from smart locks. Massive data is continuously collected, analyzed, and displayed on real-time maps with machine learning. Urban events could be detected and predicted with intelligent models. The city would become much more intelligent with autonomous driving, public WiFi, smart healthcare, and other technical elements.

Challenges and Open Issues

Generally speaking, the convergence of IoT and AI has brought a series of opportunities for both social and economic developments. Scenarios such as smart homes, intelligent transport, and smart manufacturing are all representatives that are successfully influenced by advanced AI technologies. However, it is worth noting that the convergence of IoT and AI also leads to open issues and challenges.

On one hand, the security and privacy issues are the most fundamental challenges during the convergence. Due to the fact that data serves as the core part of both IoT and AI, leaks of sensitive information will suffer from greater risks and threats. In particular, with the vulnerabilities and weaknesses of AI algorithms, there are more risks regarding security and privacy issues. How to guarantee security from end to end is one of the issues that should be emphasized during the convergence between IoT and AI.

On the other hand, the convergence of AI may challenge existing IoT architecture. The traditional IoT only focuses on establishing interconnections between fragmented things, while with the convergence of AI, IoT needs to pay much more attention to intelligence. Hence, it will drive a new wave of industrial revolution, in which countries and companies all need to formulate strategies in order to gain advantages in the future market competition.

Conclusions

With the continuous explosion in data, connection, and services, IoT has been entering an era with serious challenges. Considering the contradiction between limited resources and highly demanding requirements, it is urgent to deal with such issues and achieve high efficiency with exist-

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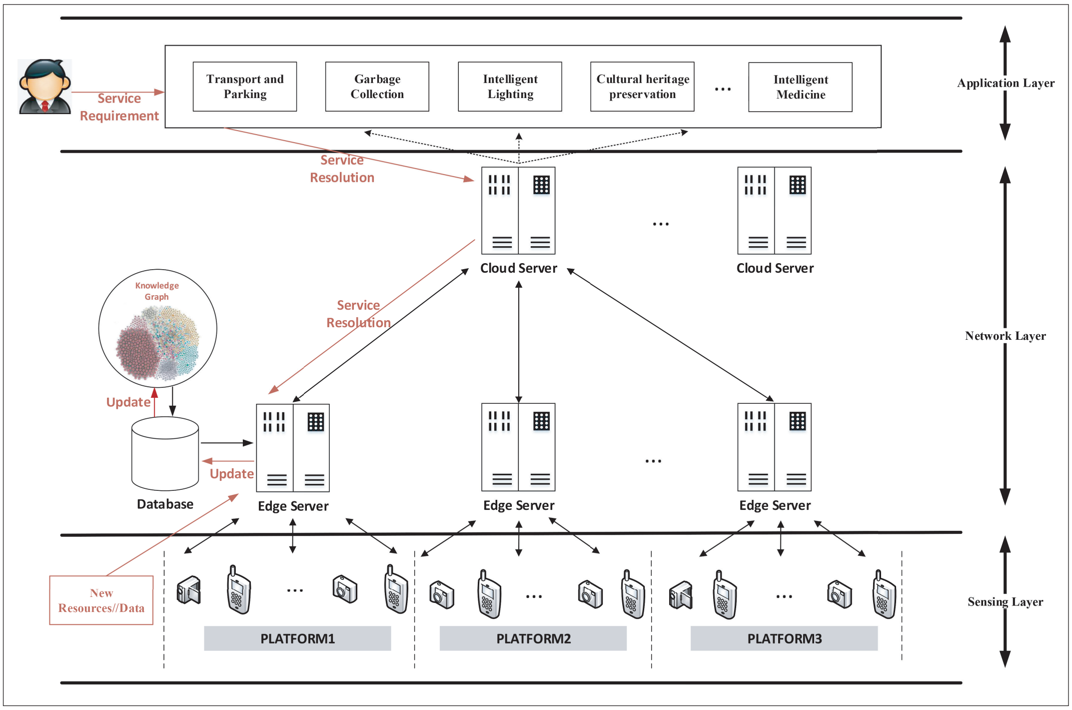

FIGURE 5. A case study of the cross-platform applications in smart cities.

ing infrastructures. In this article, we propose the concept of the convergence of IoT and AI, and give an overview of its recent progress from the sensing layer, network layer, and application layer. In addition, a pervasive case study of smart cities is demonstrated for proving the great significance of convergence between AI and IoT. Ultimately we point out open issues and challenges that are worth further study.

Acknowledgments

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