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Research progress of quantum artificial intelligence in smart city

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Abstract: The rapid accumulation of big data in the Internet era has gradually decelerated the progress of Artificial Intelligence (AI). As Moore's Law approaches its limit, it is imperative to break the constraints that are holding back artificial intelligence. Quantum computing and artificial intelligence have been advancing along the highway of human civilization for many years, emerging as new engines driving economic and social development. This article delves into the integration of quantum computing and artificial intelligence in both research and application. It introduces the capabilities of both universal quantum computers and special-purpose quantum computers that leverage quantum effects. The discussion further explores how quantum computing enhances classical artificial intelligence from four perspectives: quantum supervised learning, quantum unsupervised learning, quantum reinforcement learning, and quantum deep learning. In an effort to address the limitations of smart cities, this article explores the formidable potential of quantum artificial intelligence in the realm of smart cities. It does so by examining aspects such as intelligent transportation, urban operation assurance, urban planning, and information communication, showcasing a plethora of practical achievements in the process. In the foreseeable future, Quantum Artificial Intelligence (QAI) is poised to bring about revolutionary development to smart cities. The urgency lies in developing quantum artificial intelligence algorithms that are compatible with quantum computers, constructing an efficient, stable, and adaptive hybrid computing architecture that integrates quantum and classical computing, preparing quantum data as needed, and advancing controllable qubit hardware equipment to meet actual demands. The ultimate goal is to shape the next generation of artificial intelligence that possesses common sense cognitive abilities, robustness, excellent generalization capabilities, and interpretability.

Key words: quantum artificial intelligence; smart city; D-Wave quantum computer

1 Introduction

Smart city is a product of the new generation of information technology and economic development, which is constantly evolving and expanding its scope and meaning. The advancement of smart cities not only promotes the innovation and improvement of urban planning systems, but also enhances the economic and technological levels of the society. Artificial Intelligence (AI) applications have led to an explosive growth of data volume and an increasing complexity of algorithm models, which demand powerful computing capabilities to support them. One of the core advantages of quantum computing is its high-speed parallel computing, which enables an exponential increase of computing power. Quantum computing and AI, which were once considered incompatible like water and oil, have been integrated under the drive of science, technology, and the time, creating infinite possibilities.

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1.1 Definition of quantum artificial intelligence

Quantum Artificial Intelligence (QAI) is the product of the fusion of quantum mechanics and artificial intelligence technology. On one hand, the powerful quantum advantage is used to accelerate the upgrade and evolution of AI. On the other hand, some algorithms and technologies of AI also help solve problems in the quantum field. Qizhi Yao, an expert in quantum computing, and a winner of the Turing Prize, believes that the combination of quantum computing and artificial intelligence will be a major moment in the future. Using quantum algorithms to understand or create new intelligence will gain power beyond nature. The algorithms used in QAI is the artificial intelligence algorithm with quantum effect, such as Quantum Annealing (QA) algorithm, quantum ant colony algorithm, etc. They can overcome the defects of traditional artificial intelligence algorithm, such as easily falling into local extreme value, poor robustness, and relying on parameter training. By combining high-resolution datasets, more efficient training, and hyperparametric optimization, QAI can use traditional AI to further develop advanced physics schemes[1].

A large number of research teams have joined the quantum war, devoting themselves to the research and development of quantum artificial intelligence. In 2013, Google, the National Aeronautics and Space Administration (NASA), and the Universities Space Research Association (USRA) established the Quantum Artificial Intelligence Lab (QuAIL). In 2020, the University of Hong Kong and the California Institute of Technology founded the Hong Kong Quantum AI Laboratory. In the same year, State Atomic Energy Corporation Rosatom (ROSATOM) and the Russian Quantum Research Center announced the joint establishment of Russia's first "quantum artificial intelligence" laboratory. In 2022, Japanese Prime Minister Fumio Kishida stated that Japan would formulate a national development strategy for quantum and artificial intelligence technology.

1.2 Application of quantum computing in artificial intelligence

The unique superposition state and quantum parallelism of quantum make it exponentially faster than classical computing. Quantum computing[2] is to perform a series of unitary evolution on different quantum bits in quantum states. Quantum bit (also called qubit) is the basic unit of quantum information. Unlike classical bits, qubits can be in either the $|0\rangle$ or $|1\rangle$ states, or a linear combination of the two, which is called a superposition state. Quantum parallelism[3] refers to performing a unitary operation on 2^n quantum states in Hilbert space, which is equivalent to the simultaneous operating on all computational ground states. The advantages of many well-known quantum algorithms are exhibited by quantum parallelism, such as Deutsch–Jozsa quantum algorithm[4], Shor algorithm[5], and Grover quantum search algorithm[6].

Nowadays, the academic community has regarded artificial intelligence, which was once incompatible with quantum computing, as the focus of quantum computing. Bringing the advantages of quantum computing to the field of artificial intelligence is expected to lead to significant advances and new development directions. The breakthrough development of artificial intelligence has three elements:

(1) The core lies in the algorithm. The introduction of quantum computing is conducive to the creation of better artificial intelligence algorithms.

(2) The foundation lies in data. Quantum memory[7, 8] uses quantum coherence, one storage unit can store N quantum bits at the same time, which is conducive to the storage of big data, the construction of quantum computer, and the establishment of large-scale quantum network. With the advent of quantum storage protocol, the storage time of data can be up to 10 h, laying the foundation for long-distance communication.

(3) The advantage lies in the computing power. In the first few decades, artificial intelligence has been limited by the lack of hardware computing power, while quantum computing can increase the hardware computing power exponentially by taking advantage of its core advantages of high-speed parallel computing. This speed advantage will become more and more significant with the increase of quantum bits, reaching an unparalleled level of classical computers and effectively improving the information processing ability of artificial intelligence.

Based on the improvement of the performance of the above three elements by quantum computing, the application of quantum artificial intelligence is no longer limited to the theoretical algorithms of artificial intelligence, but also extends to the application scenarios such as cryptography design, cryptography breaking, smart city, mobile communication, machine learning, chemical and pharmaceutical, and biomedicine, accelerating the breakthrough and development of commercial applications in various fields.

1.3 Quantum computer

Although semiconductor technology has developed exponentially in the last 50 years, this state of affairs cannot go on indefinitely and will eventually succumb to the physical rules. The long-held “Moore’s law” is coming to an end, and the “post-Moore era” is coming, which has become the strategic commanding point pursued by various countries. People are eager to find more reasonable architectures, more advanced materials, and more effective algorithms. Quantum computer based on quantum effect provides a completely different computing method and architecture from classical computer, which is expected to break through the bottleneck of “Moore’s law” and become an important development direction of the “post-Moore era”. The quantum computer uses quantum bits to encode information, and uses quantum mechanics principles such as quantum state coherent superposition and quantum entanglement to realize parallel computing through quantum logic gates. Current quantum computers are divided into universal quantum computer and special-purpose quantum computer.

1.3.1 Universal quantum computer

As early as 1985, Dentsch[9], a theoretical physicist at Oxford University, defined the quantum Turing machine and proposed the design blueprint of the world’s first universal quantum computer. The universal quantum computer realizes unitary transformation through a series of quantum gate to make two controlled qubits interact. The whole quantum computing process is the time evolution process of coded qubits. The mainstream technology routes of universal quantum computer for quantum computing include superconducting qubits, ion traps, semiconductor quantum dots, nuclear magnetic resonance, etc.

Universal quantum computer can realize all quantum algorithms, and practical and effective quantum algorithms are helpful to develop the computing potential of universal quantum computer. It is the Shor algorithm[5] and Grover algorithm[6] that brought the upsurge of quantum computer research, confirmed the computing advantages of quantum computer, and promoted the accelerated development of quantum computer research.

However, due to the easy decoherence of quantum states, insufficient precision of quantum hardware, and low precision of quantum error correction, the development of universal quantum computer has made slow progress. Until today, the universal quantum computer is still in the primary stage of development, and practical killer quantum applications have not been developed yet.

1.3.2 Special-purpose quantum computer

Different from universal quantum computers constructed with quantum gate circuits, special-purpose quantum computers are generally quantum computers with quantum effects constructed for specific functions based on unique theories and models, such as optical lattice quantum simulators constructed with ultracold atom schemes, quantum computing prototypes processing Gaussian Bose sampling with optical quantum schemes, etc. Among them, the most typical special-purpose quantum computer belongs to the commercialized D-Wave special-purpose quantum computer with strong development momentum in recent years. It is an adiabatic quantum computer[10, 11]. In May 2011, Canada’s D-Wave System Company released the world’s first commercial quantum computer, D-Wave One, which indicates the arrival of the practical era of quantum computer. It is the first special-purpose quantum computer since D-Wave released 4 qubits, 16 qubits, and 28 qubits quantum annealed chips earlier this year. Since then, D-Wave has released five generations of quantum computers, including D-Wave Two, D-Wave 2X, D-Wave 2000Q, and D-Wave Advantage. The basic component of each generation of D-Waves is superconducting quantum bits (also known as SQUIDs), which are connected by couplers made of superconducting rings. The performance parameters of each generation of D-Wave quantum computer are shown in Table 1.

As can be seen in Table 1, D-Wave's quantum hardware is growing at a rapid rate, with the number of qubits doubling almost every two years. This is known as "Rose's law" in quantum computing and mimics "Moore's law" in semiconductor processor development. The latest Advantage system has become the only commercially designed and most connected commercial quantum computer in the world.

In the new Pegasus topology, qubits can be connected to another 15 qubits. Compared with Chimera topology, qubits can only be connected to another 6 qubits, and its connectivity is increased by 2.5 times. In addition, the combination of more than double the number of qubits makes it possible to solve larger and more complex problems directly on the Advantage QPU. According to the Clarity roadmap released by D-Wave, the company plans to launch Advantage2 Quantum systems with over 7000 qubits by the end of 2023 or early 2024. The D-Wave Advantage2 QPU will adopt a new qubit design to achieve 20 connections in the new topology.

D-Wave quantum computer is a special-purpose quantum computer with quantum effects, which uses quantum annealing algorithm to search the global minimum of the objective function and solve specific combinatorial optimization problems. Quantum annealing algorithm presents quantum tunneling effect, which can cross the potential barrier of energy field at near absolute zero to reach the energy minimum with greater probability, thus further approximating the global optimum solution. D-Wave performs quantum computation based on two core models, one is Ising model, and the other is Quadratic Unconstrained Binary Optimization (QUBO) model. The target Hamiltonian function can be expressed by Ising model as Eq. (1):

$$E_{\mathrm{Ising}\{s_i\}} = -H\sum_{i=1}^{N} s_i + J\sum_{\langle i,j\rangle} s_i s_j \tag{1}$$

where H represents the weight of qubits, J represents the energy coupling strength between qubits, and s_i and s_j represent the binary variable Ising spin. By transforming s_i in Eq. (1) with $s_i = 1-2x_i$, the Hamiltonian function represented by the QUBO model can be obtained:

$$E_{\mathrm{QUBO}\{x_i\}} = \sum_{i} Q_{ii}x_i + \sum_{i<j} Q_{ij}x_i x_j = x^{\mathrm{T}}\cdot Q\cdot x \tag{2}$$

where x represents the vector containing N binary variables, and Q is the $N\times N$ real upper triangular matrix describing the relationship between variables. Equations (1) and (2) show that the Ising model and the QUBO model are equivalent. In general, any optimization problem that the objective function can map to the Ising model or QUBO model can be solved by using D-Wave.

As the world's first commercial supplier of quantum computers, D-Wave's systems are already being used by some of the world's most advanced organizations, They included arms giant Lockheed Martin, Google, Temporal Defense Systems (TDS), Volkswagen, DENSO Corporation; Oak Ridge National Laboratory (ORNL), Los Alamos National Laboratory (LANL), NASA, the Germany Forschungszentrum Jülich, and

Table 1 Performance parameters of D-Wave quantum computer.

Edition	Number of qubits	Release time	Coupler per qubit	Graph topology	Josephson junction	Number of couplers
D-Wave One	128	May 2011	6	Chimera	24 thousand	352
D-Wave Two	512	May 2013	6	Chimera	33 thousand	1472
D-Wave 2X	1024	August 2015	6	Chimera	128 thousand	3360
D-Wave 2000Q	2048	January 2017	6	Chimera	128.472 thousand	6016
D-Wave Advantage	5000+	September 2020	15	Pegasus	1 million+	35 000+

other institutions; Tohoku University, Virginia Polytechnic Institute and State University, University of Southern California, and other universities.

More and more investors see D-Wave's potential. In 2013, Bezos Expeditions, an investment company under the founder of Amazon, and In Q Tel, an investment company under the Central Intelligence Agency (CIA), invested 30 million US dollars in D-Wave. In 2015, D-Wave completed a round of financing of 29 million Canadian dollars (approximately 23.1 million US dollars). In 2016, D-Wave received 30 million US dollars in investment from Fidelity Investment and the Public Sector Pension Investment Board (PSP). PSP Investments invested an additional 50 million US dollars in D-Wave in 2018. In 2019, Japan's NEC Corporation invested 10 million US dollars in D-Wave and helped develop its software. Besides, Kensington Technology Group and 180 Degree Capital Corp. Company, Goldman Sachs, Draper Fisher Jurvetson (DFJ), Business Development Bank of Canada (BDC), Penderfund Capital Management, and International Investment & Underwriting are all investors in D-Wave.

Thanks to D-Wave's powerful quantum computing system, advanced quantum products, and friendly service platform, D-Wave users have developed over 250 early applications to solve problems such as finance[12], machine learning[13], mathematical computing[14], materials science[15], biochemistry[16], layout planning[17], power energy[18], transportation[19], and healthcare[20].

2 Collision between quantum computing and artificial intelligence

People use artificial intelligence to optimize the performance of computer algorithms based on data or experience, often involving a large number of "input output" pairs, which requires artificial intelligence algorithms to be very efficient in processing these big data[21]. Facing the situation that the computing power of classical computing is rapidly approaching the limit, quantum computing is often used to solve machine learning tasks with large amounts of data due to its ability to manipulate a large number of high-dimensional vectors. Quantum computing methods used in artificial intelligence can be divided into two categories due to the difference in their operating equipment:

(1) Involving the preparation, storage, and operation of quantum states, which are used in general quantum computer.

(2) Based on the principle of adiabatic quantum computation, it is used in a special-purpose quantum computer for D-Wave[22].

Quantum artificial intelligence research collaborates quantum algorithms with artificial intelligence algorithms to process massive data tasks in order to achieve exponential acceleration over classical algorithms. In addition, QAI methods also have the ability to enhance intelligent data mining and provide significant security advantages for data owners[23].

The improvement standard of quantum artificial intelligence to classical artificial intelligence is usually measured from four aspects: computational complexity, sample complexity, robustness to environment, and model complexity[24]. Researchers have studied the improvement of classical artificial intelligence by quantum computing from the aspects of quantum supervised learning, quantum unsupervised learning, quantum reinforcement learning, and quantum deep learning. This section will also elaborate quantum artificial intelligence from these four aspects.

2.1 Supervised learning

In supervised learning, the machine uses examples of known labels to infer functions from a set of training examples. Unsupervised learning looks for hidden structures in unlabelled data. Among them, supervised learning can be divided into regression analysis and statistical classification. In order to solve the classification problem, in 2019, IBM team used the space of quantum states as the feature space, proposed two quantum algorithms based on superconducting processors. They conducted a large number of verification experiments, achieved a breakthrough in supervised machine learning for image recognition tasks[25]. In order to train supervised learning of quantum circuits, Nghiem et al.[26] proposed a general framework based on embedding in 2020, and classified two different types of methods, implicit and explicit. The authors described the implicit and explicit methods of quantum supervised learning in detail, conducted numerical simulation without noise and with noise, and conducted classification tests on several IBM Q devices. The test results show that both explicit and implicit methods exhibit good classification ability. Common algorithms of supervised learning include Support Vector Machine (SVM) and K-Nearest Neighbors (KNN). Kernel-based SVM is a nonlinear classification method suitable for classification and regression problems. Willsch et al.[13] replaced the linear classifier with a kernel-based support vector machine, expressed the problem to be optimized as a QUBO, and conducted training on D-Wave 2000Q quantum computer. The authors found that D-Wave 2000Q generates a different set of solutions, including not only the global optimal solution, but also a number of sub-optimal solution distributions that are close to the optimal solution. Especially in the case of limited training data, the performance of support vector machine is better than that of classical computer. Liu et al.[27] strictly proved that the heuristic quantum kernel method can achieve end-to-end exponential quantum acceleration for specific learning problems through the classification problem constructed in 2021. The authors constructed a series of datasets, and proved that no classical algorithm can classify the data better than random guess. The experimental results lay a theoretical foundation for applying quantum advantage to machine learning.

2.2 Unsupervised learning

Unsupervised learning obtains useful information of new samples by training the model of dataset structure used for learning. It is suitable for the lack of prior knowledge or difficult to manually label categories. However, because of this reason, unsupervised learning sometimes has the problem of low efficiency and some tasks are difficult to complete. Researchers have introduced quantum computing technology into the improvement and optimization of common unsupervised learning, such as clustering, feature extraction, manifold learning, data dimensionality reduction, etc.

In 2018, Neukart et al.[28] proposed a Quantum-Assisted Clustering Analysis (QACA) based on the topological characteristics of D-Wave 2000Q quantum processor. With the support of Quantum Processing Unit (QPU), optimization, sampling and clustering were expressed in the form of QUBO. Experiments show that QACA is equivalent to classical clustering algorithm in accuracy, but different results will be obtained due to different clustering forms. In 2019, Moshkbar-Bakhshayesh and Pourjafarabadi[29] proposed a transient identification method for Nuclear Power Plants (NPPs) based on online Dynamic Quantum Clustering (DQC) using quantum mechanics. Provide data for each event to DQC to form a cluster independent of other transients, and label all formed clusters based on their associated transient names. With the passage of time, each new data are finally in an appropriate cluster, so that the type of transient can be identified online. The authors used Singular Value Decomposition (SVD) and bipolar representation of real data to reduce the dimensionality of the data and clearly display the positive and negative aspects of the information. The results indicate that DQC is suitable for classification of potential wells with sufficient spacing or transient situations with superimposed small noise.

Unsupervised learning algorithm has the problem that it cannot complete in polynomial time when facing some large datasets. In 2020, Shrivastava et al.[30] analyzed the feasibility of quantum equivalent classical machine learning algorithm to enhance the computing power of unsupervised learning algorithm. The authors expounded the classical unsupervised learning algorithms such as principal component analysis, manifold embedding, and clustering algorithm, put forward the equivalent quantum versions of these algorithms, and inferred the computational complexity through mathematical representation. By comparing the quantum version with the classical version, it is proved that the quantum unsupervised learning algorithm equivalent to the classical algorithm provides a secondary acceleration in learning efficiency and an exponential acceleration in computational complexity.

In 2021, Deville and Deville[31] defined the general concept of SIngle-Preparation Quantum Information Processing (SIPQIP). It is used as a general quantum information processing framework for processing various quantum information tasks and evaluating numerical performance. The authors showed a concrete example of applying the proposed method to the tasks related to spintronics and proposed two quantum system structures to compensate for the Heisenberg coupling between qubits. In 2022, Schmitt and Lenarčič[32] introduced a method for analyzing the local complexity of quantum multi-body based on machine learning, which is composed of unsupervised learning and automatic encoder. Unsupervised learning trains the expected values of the data to obtain dimensionality reduction, revealing the existence of effective low dimensional descriptions for multi body quantum states; automatic encoder extracts the physical related features of quantum multi-body by solving the unsupervised learning task of local observation.

2.3 Reinforcement learning

With the introduction of AlphaGo and AlphaZero[33, 34] which combine reinforcement learning, neural network, and Monte Carlo tree search, reinforcement learning has become an important example in artificial intelligence, and its theory and algorithm have developed rapidly. In the reinforcement learning framework, agents interact with the environment and constantly update their behaviors according to the rewards they get to maximize their benefits. Reinforcement learning has emerged in competitive game, intelligent control, health care, natural language processing, and other practical applications. But in its development, there are many problems such as long agent training time, difficulty in designing reward functions, low sampling efficiency, and easy to fall into local suboptimal solutions. Therefore, researchers try to solve or reduce the above defects with quantum advantages.

In 2017, Levit et al.[35] introduced the concept of Free Energy-based Reinforcement Learning (FERL) to study the applicability of quantum annealing machine in reinforcement learning. And it is used in D-Wave 2000Q for reinforcement learning of grid-world problem. The authors used the ability of quantum sampling in the reinforcement learning task, and achieved better performance than deep Q-Network (DQN) in a certain scale of problems, and considered that it could be extended to solve larger-scale reinforcement learning tasks. In 2020, Ayanzadeh et al.[36] combined reinforcement learning (more specifically, learning automata) with quantum annealing algorithm and proposed Reinforcement Quantum Annealing (RQA) scheme to improve the quality of results obtained by quantum annealing. In this scheme, the agent maps the Boolean Satisfiability Problem (SAT) to the executable Quantum Machine Instruction (QMI), interacts with the D-Wave quantum computer, and attempts to iteratively minimize the Hamiltonian for the SAT problem. The experimental results show that compared with the latest quantum annealing technology, the RQA scheme can find better solutions with fewer samples. In 2020, Neumann et al.[37] introduced multi-agent reinforcement learning based on free energy, which was based on Suzuki-Trotter decomposition and Simulated Quantum Annealing (SQA) sampling. On this basis, the algorithm was extended to any number of agents with quantum Boltzmann machine to realize the modeling of arbitrary grid-world problems. The experimental results show that quantum annealing can improve the efficiency of reinforcement learning, and can find a high-fidelity scheme faster than classical reinforcement learning. In order to clone the unknown quantum state to high fidelity, Shenoy et al.[38] cloned the unknown environmental state to the agent qubit in IBM’s Quantum Assembly Language (QASM) simulator in 2020 based on the quantum reinforcement learning protocol. The experimental results show that this method can obtain a high ratio of fidelity when there are only limited copies of the equivalent substate. In 2021, Saggio et al.[39] proposed and demonstrated a new reinforcement learning protocol. The agent can accelerate its learning speed through quantum communication with the environment, realize quantum acceleration, and achieve optimal control of the learning process. This learning protocol is realized by using a compact and fully adjustable integrated nanophoton processor and electronic communication wavelength subinterface.

2.4 Deep learning

The concept of deep learning originates from the research of artificial neural network, which uses multiple processing layers to express, learn, classify, and recognize data features[40]. Because of its strong learning ability, strong adaptability, good portability, automatic feature extraction, suitable for big data processing, and other advantages, deep learning has far exceeded the performance of classical machine learning in some applications. It has been applied to image processing, fault diagnosis, data mining, natural language processing, character recognition, and other fields. However, it still has some defects, such as large computation, poor interpretability, and complex model design. Therefore, it is necessary to introduce quantum technology to optimize traditional deep learning.

In 2016, Wiebe et al.[41] proved through experiments that quantum computing could reduce the training time of deeply restricted Boltzmann machines, improve training efficiency, provide higher-quality models and frameworks than classical computing, and optimize basic objective functions. The quantum deep learning framework proposed by the authors can refine the mean field approximation to a state close to the desired Gibbs state, and process it in parallel on multiple quantum processors to improve computational power. To evaluate the feasibility of using D-Wave as a machine learning sampler, in 2020, Sleeman et al.[42] described a hybrid system that combines classical deep convolutional self-coding neural networks quantum annealing Restricted Boltzmann Machine (RBM). The system overcomes the limitations of D-Wave's finite qubits and sampling only binary information, and uses the inherent noise and quantum properties of D-Wave to map the original data representation to the representation of quantum annealing processing. Based on Modified National Institute of Standards and Technology (MNIST) dataset and MNIST Fashion dataset, the authors realized image compression, and used downstream classification method to evaluate and confirm the performance advantages of the proposed system. Autonomous Vehicles (AVs) under adversarial attacks may misrecognize traffic signs, jeopardizing driving safety. In 2021, Majumder et al.[43] used classical quantum learning model and adversarial deep learning model to design a hybrid classical quantum machine learning model to resist adversarial attacks. The output of a classical processor is further processed through a quantum layer made up of various quantum gates. The mixed model has better elasticity and classification accuracy than the classical model. Quickly and accurately analyzing and diagnosing power faults can avoid power outages and abnormal changes in voltage and current. In 2021, Ajagekar and You[44] proposed a hybrid framework for identifying power system faults by combining conditional Constrained Boltzmann Machine (CRBM) with deep network. By complementing quantum and classical techniques, the computational complexity of classical learning algorithm for CRBM networks is overcome. An example study on the fault diagnosis framework of hybrid Quantum Computing-Conditional Restricted Boltzmann Machine (QC-CRBM) is carried out on IEEE 30-bus test system. The applicability of this framework is proved. Compared with traditional training methods and advanced pattern recognition methods, the hybrid QC-CRBM fault diagnosis framework also shows better performance. In 2023, Higham and Bedford[45] combined the classical neural network with the quadratic binary model, constructed the task to be classified into a quadratic binary model, and sent this model to D-Wave for quantum annealing. The QPU solves the two obstacles that limit the scale expansion: the number of variables required for the model state and the binary property. The test results based on digital image data show that this method has the potential to accelerate the classification task by at least one order of magnitude.

Quantum artificial intelligence fills the gap between quantum computing theory research and artificial intelligence application science. It is a rapidly developing field with the ability to develop future AI applications. With the development of quantum computing technology, various research fields of quantum artificial intelligence are expected to bring revolutionary changes to information data processing in the future.

3 Quantum artificial intelligence empowers smart city

Sensors distributed throughout smart cities are constantly producing data. According to the report “Data Age 2025: The Evolution of Data to Life Critical” released by the international data company IDC, the amount of data generated globally each year will increase from 33 zettabytes in 2018 to 175 zettabytes. It is equivalent to generating 491 exabytes of data every day. Processing, analyzing, and storing these data pose a further challenge to information processing technology. Since IBM put forward the concept of smart city in 2008, thanks to the support of computer technology, communication technology, sensor technology, and other advanced science and technology, the field of smart city has made great progress in the width and breadth of application scenarios. At the same time, there are still many problems in the construction of smart cities, such as resource dispersion, imperfect safety system, environmental pollution, and traffic congestion, which have become bottlenecks restricting the current urban development and transformation. Human beings have begun to focus on quantum computing, hoping that quantum information technology can bring a positive impact on smart cities.

3.1 Intelligent transportation

Using quantum algorithm, quantum artificial intelligence has shown quantum advantages in path planning, transportation facilities layout, vehicle operation management, driver behavior, and other issues[46]. Thanks to the commercial D-Wave quantum computer, some intelligent transportation projects have been applied in practice. For example, at the Web Summit conference held in Lisbon in 2019, Volkswagen Group used D-Wave quantum computer to conduct quantum navigation tests on 9 buses, providing traffic guidance for thousands of passengers. In 2020, Wang et al.[47] built a Quantum & Brain-Inspired Hybrid-Computing Framework (QBIHCF) by combining quantum annealing algorithm, brain-inspired cognitive science, and classical computing, and proposed the Quantum & Brain-Inspired Clustering Algorithm (QBICA). Quantum annealing algorithm is used to improve search efficiency, and brain-inspired cognition extracts data pattern features to provide search direction and search feedback. By comparing the experimental results with K-means algorithm, it is proved that QBIHCF architecture based on QBICA can realize effective traffic diversion, overcome the dependence on training samples and the sensitivity of small sample data, and provide a new idea for realizing robust quantum artificial intelligence. In 2022, under the guidance of intuitive reasoning, the research group introduced selective attention mechanism and realized the asymptotically optimal location of public parking lot by using the quantum tunneling effect of quantum annealing algorithm[48].

Universal quantum computer has not been applied yet, so its application in the field of intelligent transportation is mostly limited to using quantum states and quantum algorithms to improve the transportation scheme. In 2020, Xiao et al.[49] adopted the quantum secret sharing method to improve communication efficiency between vehicles, especially in the presence of potential adversaries and malicious vehicles. This scheme encodes traffic control information in an orthogonal quantum state and periodically shares it among cooperating cluster-head vehicles. In the same year, Zhang et al.[50] combined quantum genetic algorithm with learning vector quantization in order to accurately predict the short-term flow of urban traffic. Benefiting from the advantages of Learning Vector Quantization (LVQ) neural network’s simple structure and good clustering performance, they utilized quantum genetic algorithm to compensate for the shortcomings of LVQ neural network’s sensitivity to initial values and susceptibility to local minima[50]. The performance advantages of the Quantum Genetic Algorithm Learning Vector Quantization (QGA-LVQ) neural network have been confirmed through comparative experiments.

3.2 Improve urban operation support capacity

Urban operation guarantee ability has always been one of the main indicators to measure the livability and wisdom of a city. It is also an important item in the overall planning of urban economic and social development. Quantum technology has been applied to medical care, logistics, communications, and other urban security.

(1) Medical security

In order to build a more efficient medical environment, Naresh et al.[51] proposed a three-layer medical system architecture called Intelligent Medical City in 2020, introducing Multi-Agent System (MAS) to improve medical efficiency. Meanwhile, in order to protect the quality of electronic healthcare in smart cities and resist quantum-based attacks, Naresh et al.[51] also proposed a Quantum Group Key Agreement (QGKA) based on Quantum Diffie Hellman (QDH) technology, extended QGKA to Dynamic QGKA (DQGKA) by adding join, and left protocols and other operations. By comparing this protocol with existing QGKA protocols in terms of Qubit Efficiency (QE), Unitary Operation (UO), Unitary Operation Efficiency (UOE), Key Consistency Check (KCC), and Security Against Participant (SAP) attacks, the excellent performance of this protocol was verified.

In the same year, in order to alleviate the scheduling problem of doctors and nurses caused by the COVID-19 pandemic, Das et al.[52] described the objective function as Ising model under different constraints for the Nurse Scheduling Problem (NSP), the Physician Scheduling Problem (PSP) and the Nurse-Physician Scheduling Problem (NPSP). And it is converted into the QUBO model. The solutions obtained by classical (simulated) temperers and D-Wave 2000Q forward and reverse temperers are compared and analyzed. It is found that the reverse annealing method always gives the best output for each scheduling problem. This system can still provide accurate solutions for different numbers of medical staff, with great flexibility and practicality.

(2) Logistics support

D-Wave is not only used in medical security, but also in logistics support system. In 2020, Japan's Groovenauts, Inc. cooperated with Mitsubishi Estate Co., Ltd., based on the data provided by Mitsubishi Estate and cloud service MAGELLAN BLOCKS, and adopted a quantum hybrid solution formed by machine learning provided by MAGELLAN BLOCKS and D-Wave quantum computing technology to optimize garbage collection and transportation routes, so as to improve operational efficiency and reduce carbon dioxide emissions.

(3) Security guarantee

Target tracking technology is often used in video surveillance, vehicle control, human-computer interaction, and other problems in smart cities. Particle filtering is one of the common methods in target tracking, which inevitably meets the problem of particle degradation. In 2020, Liu et al.[53] introduced quantum genetic algorithm into particle filters and proposed Quantum Genetic and Particle Filter (QGPF) algorithm. This algorithm not only solves this problem, but also utilizes the parallelism of quantum to improve real-time tracking. The standard Particle Filter (PF) algorithm, Particle Swarm Optimization Filter Algorithm (PSOPF), and QGPF are simulated and compared through nonlinear target tracking model and time setting model, and the high accuracy and good numerical stability of QGPF algorithm are confirmed.

3.3 Sustainable urban planning

The use of intelligent control methods and the construction of smart grids on information platforms has become an important support for the construction of smart cities. In today's increasingly increasing electricity load, understanding the electricity characteristics of residents can help urban planners more accurately grasp urban electricity information and make more reasonable layouts. As early as 2015, Guo et al.[54] aimed at the shortcomings of traditional Fuzzy C-Means (FCM) in power load pattern extraction, replaced the original iterative optimization process of FCM with the particle swarm optimization based on quantum coding. This method has obtained more reasonable clustering results, laying the foundation for more accurate and effective electricity identification.

In order to build a people-oriented smart city and satisfy people's real life and spiritual aesthetics, urban landscape planning has always been an important part of urban construction. In 2020, Yao and Ding[55] introduced an improved quantum behaved particle swarm optimization (hybrid improved Quantum-Behaved Particle Swarm Optimization (LTQPSO)) to plan the path for the typical landscape footpath construction. The construction cost of landscape trail is reduced. LTQPSO algorithm avoids the precocious convergence problem of particle swarm optimization algorithm, and enhances the global search capability and speeds up the convergence by introducing natural selection method into the traditional position updating formula.

3.4 Information communication

Based on the uncertainty principle, measurement collapse, and non-cloning theorem in quantum mechanics, quantum provides protection for the security of information communication in smart cities that cannot be cracked by computation. Quantum communication is divided into quantum teleportation and quantum key distribution. The former utilizes quantum entanglement effect, while the latter utilizes quantum non-cloning and measurement randomness. At present, many aspects of quantum communication, such as the design and optimization of quantum communication protocols, are still in the manual processing stage, which prolongs the cycle and increases the cost. The introduction of artificial intelligence technology is helpful to alleviate the above problems and improve the performance of quantum communication in smart cities. Although the universal quantum computer has not yet reached the level of practical application, it has become more mature as a secure and reliable information communication, and researchers have carried out in-depth research on it.

3.4.1 Mobile communication

Benefiting from the principles of quantum mechanics and the unique properties of quantum teleportation[56], quantum mobile communication has become one of the direction of human future communication development. It has advantages such as fast speed, large capacity, and high security that traditional communication methods cannot match. At the same time, there are still some defects, such as many technical obstacles, high implementation difficulty, and high computational complexity which hinder its development.

In 2013, aiming at the (Non-deterministic Polynomial)-Hard (NP-Hard) problem of computational complexity of maximum likelihood detection, Chao Wang's team applied quantum Grover algorithm and Grover–Long algorithm to signal detection in VBLAST system[57]. The MATLAB simulation results show that the detection performance of Grover algorithm is close to that of maximum likelihood detection when the search error is large. When the search error is small, the original Grover algorithm fails to search, while Grover–Long algorithm can still approach the maximum likelihood detection performance, and the computational complexity has the effect of square acceleration. This team also applied quantum ant colony algorithm to Multiple-Input Multiple-Output (MIMO) system in 2016, and proposed a signal detection scheme of MIMO system based on quantum ant colony algorithm[58]. The simulation results show that the computational complexity of the scheme is polynomial and the detection performance is close to that of maximum likelihood detection in arbitrary modulation mode. On 16 August 2016, China successfully launched the world's first quantum science experiment satellite "Quantum Experiments at Space Scale", realizing quantum communication between the satellite and the ground[59−61]. With the quantum satellite, Chinese researchers have successfully carried out three major scientific experiments: quantum entanglement distribution, quantum key distribution, and quantum teleportation.

3.4.2 Quantum Internet

With the continuous development of quantum computer, the demand for quantum Internet that can provide secure communication and all network functions of traditional Internet is increasingly urgent. Quantum Internet is a network that realizes quantum communication between any two quantum devices on earth through quantum links and classical quantum devices[62]. Because the quantum Internet is controlled by the quantum mechanics theorem, there are no corresponding phenomena in some classical networks, such as non-cloning theorem, quantum entanglement, decoherence, quantum teleportation, quantum measurement, and so on, which bring obstacles and challenges to the design of the quantum Internet[63]. Quantum Internet[64, 65] is mainly composed of quantum channels, quantum repeaters, and terminal nodes, and has been deployed in secure communication, quantum sensor networks, clock synchronization, and other applications.

In order to optimize the construction of wireless video sensing networks in smart cities, Fan et al.[66] proposed a network optimization coverage algorithm in 2015. Based on quantum genetic algorithm, this algorithm achieves the maximum effective coverage in large area and complex monitoring area with good convergence and fast operation speed. The article introduces two limit values of ideal node coverage and ideal node weighted coverage, and uses relative comparison method to evaluate and support the experimental results. The quantum memory failure event in the quantum Internet can disrupt several entangled connections in the entangled network, which may have serious consequences in the relay network. To address this issue, Gyongyosi and Imre[67] proposed a dynamic adaptive routing method suitable for practical quantum networks in 2019. This method finds the shortest node-disjoint replacement path between the source quantum node and the target quantum node, and uses this replacement path as a temporary path until all broken connections between the repeater nodes are re-established. The shortest path is determined in a decentralized manner by an underlying graph covering all the information in the quantum network to provide an efficient computational solution. In the same year, Gyongyosi and Imre[68] defined a method to realize controlled entangled access in quantum Internet, which can provide users with entangled access with different priorities. This model uses the path between the source node and the target node as the path cost function, and takes the reliability (probability) of entanglement connection and the entanglement fidelity coefficient as the main indicators to achieve entanglement discrimination. This scheme can be applied to entangled quantum networks of quantum Internet. According to the dynamics of entangled quantum networks, in 2020, Gyongyosi[69] developed a mathematical model that can characterize the stability, fluctuation properties, and dynamics of entangled flows, so as to quantify the structure of entangled networks and the dynamics of entangled flows in quantum Internet. This study provides the basic definition and terminology of quantum entangled network dynamics in quantum Internet, evaluates and quantifies the dynamics of entangled network structure in quantum Internet, proves the equilibrium state of entangled quantum network structure, and studies the influence of noise on the stable equilibrium state of entangled network. Because the established model is independent of the actual physical realization, it can be applied to the heterogeneous structure of the global quantum Internet. In order to solve the additional complexity of entanglement distribution caused by the introduction of quantum repeater, Goodenough et al.[70] developed an algorithm in 2021, which can effectively perform heuristic optimization on subsets of quantum repeater schemes of universal repeater platforms in different scenarios. Since this algorithm is not specific to any specific experimental settings, it can be applied to three experimental quantum repeaters, such as information processing platform, multiplexing basic pair generation platform, and the combination of the two to achieve the impact on the entanglement distribution ability. Moreover, the algorithm can also be used to explore the parameters of the near deterministic entanglement distribution on the repeater chain.

3.4.3 Quantum routing

Quantum routing realizes the transmission of quantum information in different quantum tunnels and quantum networks through the regulation of quantum signal transmission. Quantum routing can provide path selection for quantum information communication without changing the transmitted quantum state information. It is an important quantum device in full quantum network.

In 2019, Pant et al.[71] proposed an improved routing protocol that could generate simultaneous entanglement among multiple pairs of users in a quantum network. By utilizing the diversity of multipath in the network, two users gain a great gain in the entanglement rate. In addition, the authors also proposed and analyzed the quantum repeater protocol, taking into account the channel loss between repeater nodes and the probability properties of Bell state measurement. In order to realize quantum entanglement between two parties of remote communication, Shi and Qian[72] studied entanglement routing in the same year and proposed a new quantum network entanglement routing model. The model aims to establish remote entanglement for a pair of source and destination through multiple hops, reflecting the difference between quantum networks and classical networks. In addition, the authors proposed a Quantum Contention-free pAth Selection at runTime (Q-CAST) algorithm based on the unique characteristics of quantum networks, which greatly increases the number of successful long-range entanglements. In 2019, Chakraborty et al.[73] studied distributed routing in quantum Internet, modified existing classical distributed routing algorithms to develop new routing algorithms for quantum networks containing noisy quantum devices, and applied these algorithms to continuous models and on-demand models. To reduce network delay and satisfy entanglement between two nodes at a distance, a special quantum network with pre-shared entanglement link is proposed. At the same time, the performance of routing algorithms in ring, grid, and recursively generated network topologies is studied, and the ring and grid topologies are numerically simulated. Also in 2019, in order to solve the network delay problem in multi-party simultaneous communication, Hahn et al.[74] proposed a method of realizing remote synchronous communication using graph state. The authors discussed how to find algorithms that can be implemented in polynomial time for structured resources of specific classes when the general problem is NP complete. All schemes are based on local complementarity, helping to reduce the number of measurements required in quantum routing schemes and achieve better performance than standard repeater schemes. In 2021, Bapat et al.[75] utilized existing methods to quickly reverse the order of qubits and proposed a method to achieve arbitrary arrangement of qubits. They proposed the generic divide and conquer with adaptive Tripartite Binary Sort (TBS) to sort binary strings algorithm[75]. Through experiments, the authors confirmed that the performance of using fast state reversal primitives for routing in worst-case and average scenarios is better than any swap based protocol; quantum routing algorithms perform better than any exchange-based protocol in both worst-case and average scenarios, demonstrating the first quantum acceleration of unitary quantum routing. Optical quantum routing is the quantum node of optical quantum networks, responsible for providing basic data processing and routing functions. In the same year, Li et al.[76] proposed a method for achieving single photon routing at different frequencies. By designing the number of embedded emitters, the structure of scatterers, and the cavity-emitter interaction, this method can design the routing peak of photons and control the routing ability of photons with different frequencies. The authors conceived a quantum photon routing scheme, which uses the terminal channel to control the propagation direction of photons.

4 Conclusion

The rapid development of artificial intelligence is constrained by the massive amount of data computation and storage, and traditional servers cannot satisfy the need for parallel computing power. Besides improving the performance and efficiency of artificial intelligence computing systems, it is also necessary to explore new technologies that can enhance computing power. Quantum, as a universal technical method, has great adaptability.

When quantum is applied to computation, it becomes quantum computation; when quantum is applied to communication, it becomes quantum communication; when quantum is applied to artificial intelligence, it forms QAI. QAI benefits from the strong quantum advantages, which are expected to break the bottleneck of AI and support the revolutionary development of AI computing power and storage. Compared with traditional artificial intelligence, quantum artificial intelligence can use quantum effects to improve search efficiency and operation speed, and overcome the drawback that traditional algorithms are prone to get stuck in local optima.

The integration of quantum computing and artificial intelligence is still in the initial stage, and it faces challenges at different levels:

(1) Design quantum artificial intelligence algorithm

If traditional artificial intelligence algorithms are implemented on quantum computers, they can only execute serial computations, which does not utilize the quantum advantages of the hardware. Therefore, to facilitate parallel computing and to harness the superior computational power of quantum computing, it is imperative to design quantum artificial intelligence algorithms that are tailored for quantum computers.

(2) Build a hybrid architecture of quantum-classical computing

From the standpoint of current technology, quantum computing cannot entirely supplant traditional computing. Instead, there exists a state of mutual enhancement, parallel advancement, and cross-integration between the two. Viewing the quantum processor as a co-processor to classical computing can help address some of the limitations of traditional artificial intelligence, such as dependence on training data, lack of robustness, and absence of cognition. The construction of a hybrid model that combines quantum and classical computing can lead to efficiencies where the whole is greater than the sum of its parts, paving the way for exploration into deeper and broader application fields.

(3) Preparing quantum datasets

Quantum data, characterized by entanglement and superposition, differ significantly from classical data. Storing and processing such data with a traditional computer necessitates an exponential amount of resources. Therefore, generating the required quantum data using quantum computers or other quantum mechanical equipment has become a primary area of research in the era of big data.

(4) Increase the number of controllable qubits in quantum computer

As of now, the controllable quantum bit quantity of the universal quantum computer is represented by the 127 quantum bits held by the quantum computer “Eagle” developed by IBM. For the special-purpose quantum computer, the D-Wave Advantage quantum computer announced by D-Wave Company contains more than 5000 qubits. This is hundreds or even tens of thousands of orders of magnitude different from the millions of qubits required to solve practical problems using quantum computing.

Artificial intelligence is poised to transition into the era of quantum artificial intelligence. The ripple effects of quantum artificial intelligence across various fields are anticipated to break through existing bottlenecks. For instance, in the financial industry, it could enhance transaction efficiency and bolster fraud detection. In the realm of biomedicine, it could aid in understanding molecular structures and functions. In the energy sector, it could expedite the control and optimization of energy systems, thereby improving energy utilization efficiency, among other benefits. Looking ahead, quantum artificial intelligence is expected to not only drive the development of applications and technologies but also revolutionize existing architectures, ushering in a new wave of scientific and technological revolution.

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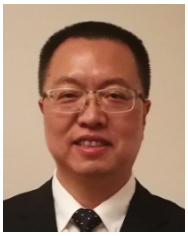

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