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A survey of quantum computing hybrid applications with brain-computer interface

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ABSTRACT

In recent years, researchers have paid more attention to the hybrid applications of quantum computing and brain-computer interfaces. With the development of neural technology and artificial intelligence, scientists have become more and more researching brain-computer interface, and the application of brain-computer interface technology to more fields has gradually become the focus of research. While the field of brain-computer interface has evolved rapidly over the past decades, the core technologies and innovative ideas behind seemingly unrelated brain-computer interface systems are rarely summarized from the point of integration with quantum. This paper provides a detailed report on the hybrid applications of quantum computing and brain-computer interface, indicates the current problems, and gives suggestions on the hybrid application research direction.

1. Introduction

Quantum computing originated in 1980. Benioff [1] attempted to use quantum mechanics to carry out reversible computation to reduce heat dissipation, while Feynman [2] proposed the concept of quantum computing independently from the perspective of efficient quantum simulation. What is rarely known is that Soviet scientist Manin [3] also put forward the idea of quantum computing at the same time. Due to its parallelism, quantum computing is more powerful than classical computing in processing and storing data. Since 1995, quantum computing has gradually become the most popular research frontier in the world, and a variety of possible schemes for realizing quantum computers have been proposed successively [4]. Fig. 1 shows three different quantum circuits used in the study of quantum computing [5].

Brain-computer interface (BCI) is a direct communication channel between the central nervous system and the computer, without the help of the peripheral nervous system [6]. In this sense, any system that has a direct interaction between the brain and external devices can be considered a BCI system. While early BCI technologies provided tools for movement disorders to communicate with the environment, the use of BCI has expanded to many medical and non-medical applications, including brain state monitoring, neurological rehabilitation, and human cognitive enhancement. With the rapid development of neurotechnology and artificial intelligence (AI), the brain signals used for communication between the brain and computer have developed from the level of sensation, evoked potential and perception, the event-related potential to higher-level cognition (such as goal-directed intention), bringing BCI into a new era of hybrid intelligence [7]. At present and in the future, BCI and quantum computing are important frontier research hot spots in the world, and scientists pay more and more attention to their comprehensive application research. Therefore, this paper will make a detailed review of the development of quantum computing and BCI.

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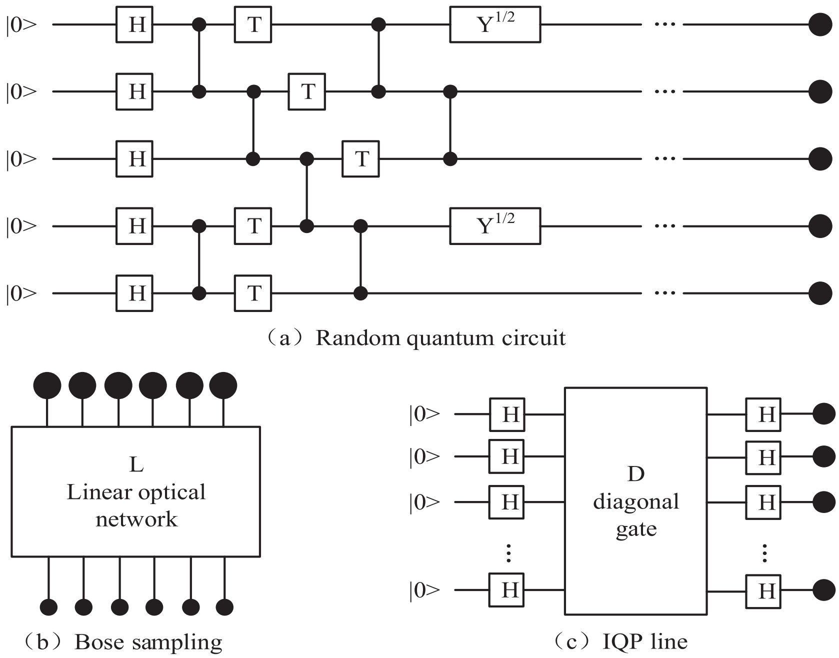

Fig. 1. Three quantum circuitsof the two. This paper summarizes the problems and shortcomings of mixed applications of quantum computing and brain-computer interfaces in the current social development. This paper also makes a conclusion and prospects for the future combination of quantum computing and brain-computer interface technology.

This paper introduces a research report on the hybrid application of quantum computing and brain-computer interface, starting from the main classification of quantum computing-related algorithms and brain-computer interfaces, then the intelligent application of quantum computing and brain-computer interfaces, and then ending with the mixed application

The rest of this review is arranged as follows, the second section mainly describes quantum computing, including the development of quantum computing and related algorithms of quantum computing, and the third section mainly describes the brain-computer interface, including the classification of the brain-computer interface and the intelligent application of brain-computer interface, and the fourth section mainly describes the application of quantum computing and brain-computer interface after mixing, including recursive quantum neural networks and intelligent control systems based on quantum soft computing. The fifth section introduces the current problems and future development directions of quantum computing and brain-computer interfaces, and the sixth section summarizes the quantum computing and brain-computer interfaces and makes prospects.

2. Quantum computing

In 1982, physicist Richard Feynman first proposed the concept of quantum computing [8]. After nearly 40 years of development, quantum information, quantum computing, and quantum simulation have made great progress, but in recent years, the development of the whole field has taken on different characteristics [9]. Fig. 2 is a diagram of the correlation structure of the quantum computation. People pay more attention to containing more than the number of qubits in quantum computing and quantum simulation, in the premise of guaranteeing the fidelity of quantum operation, to increase the number of qubits, some recent experiments involving the number of qubits to reach dozens, is close to most classical computers can simulate quantum bits, and could realize the so-called quantum advantage or hegemony [10]. However, on the other hand, there is a considerable distance between each experimental platform and the thousands of quantum bits required by practical quantum computing, and there is still room for significant improvement in the fidelity of quantum logic gates and the threshold value of quantum computing for fault tolerance [11]. DiVincenzo [12] 2000 summarized five requirements that need to be met for a potential physical system to implement quantum computing. One of the most important is that the system should have scalable qubits. Scientists have said that quantum computing and quantum information are the frontier of contemporary science and have broad development prospects [13]. The following part is mainly described two aspects of quantum algorithm and quantum computing application.

2.1. Quantum algorithms

As an emerging computing paradigm, quantum computing is expected to solve the technical problems that classical computers are difficult to solve in the fields of combinatorial optimization, quantum chemistry, information security, and AI [14]. At present, both the hardware and software of quantum computing continue to develop rapidly, but it is expected that the standard of universal

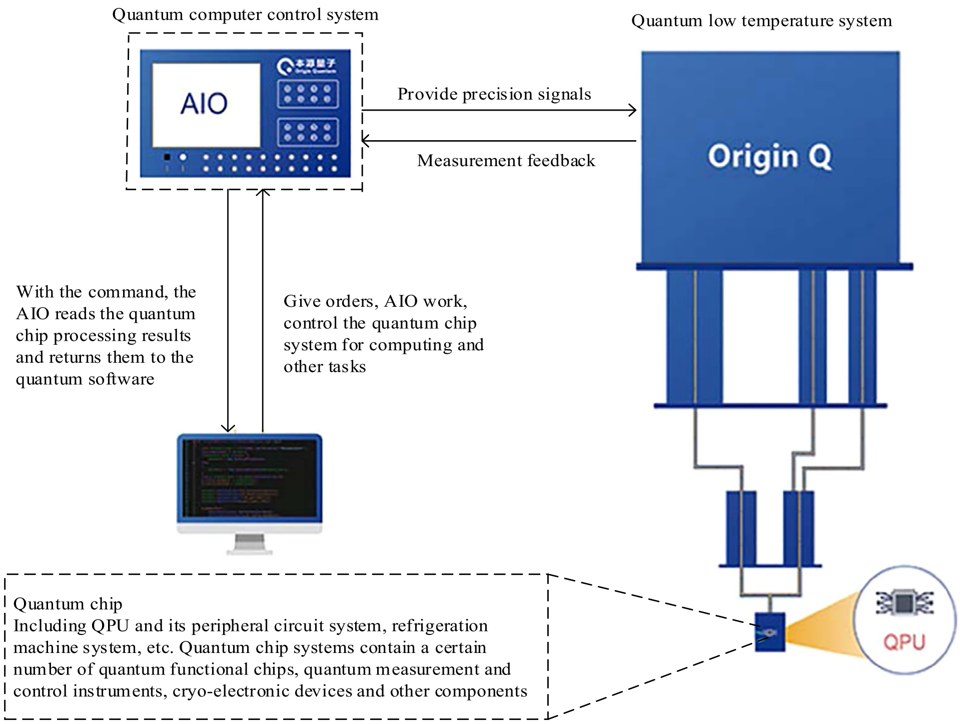

Fig. 2. Quantum computing structure diagram.

Table 1
Advantages and disadvantages of various quantum algorithms.

Name of quantum algorithm	Advantages	Disadvantages	References
Shor large number decomposition algorithm	Quantum parallel computing, greatly improves the computing speed	There is no guarantee that every run will get the right result	[19]
Harrow-Hassidimlloyd algorithm for solving linear equations	For some special linear equations, it can be exponentially faster than the classical algorithm	The cost of dealing with the problem is too high	[20]
Grover search algorithm	Compared with the traditional algorithm, it is twice accelerated	As the ratio of the number of target states to the total number of database objects increases, the search success probability of the algorithm decreases rapidly	[21]
Quantum annealing algorithm	The quantum tunneling effect generated by quantum fluctuation is used to get rid of local optimum and realize global optimization	The convergence speed is slow, the execution time is long, the algorithm performance is dependent on the initial value and the parameter is sensitive	[22]

quantum computing will not be reached in the next few years [15]. Therefore, how to use the quantum algorithm to solve practical problems in the short term has become a research hot spot in the field of quantum computing. Quantum algorithms are algorithms applied to quantum computers. For the difficult problems of classical algorithms, some quantum algorithms can be found to solve them in an effective time [16]. Some can accelerate the solution of the problem under certain conditions, thus showing the advantages of the quantum algorithm [17]. In quantum computing, a quantum algorithm is an algorithm running on the real model of quantum computing, the most commonly used model is the quantum circuit calculation model. A classical (or non-quantum) algorithm is a finite sequence of instructions, or a step-by-step process of problem-solving, in which each step or instruction can be executed on a classical computer [18].

One of the main purposes of building quantum computers is to perform quantum computing tasks, that is, to realize the operation of quantum algorithms. In past studies, various quantum algorithms have been proposed, representative of which are the Shor large number decomposition algorithm [19], Harrow-Hassidimlloyd algorithm for solving linear equations [20], and Grover search [21], quantum annealing algorithm [22], etc. The advantages and disadvantages of the algorithm are shown in Table 1. The typical Grover search algorithm is shown in Fig. 3, where each line represents a quantum bit and the quantum gate operation is represented by different squares.

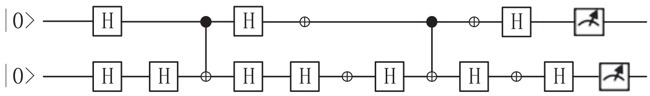

Fig. 3. Schematic diagram of the Grover algorithm.

A Quantum algorithm is a step-by-step process in which each step can be performed on a quantum computer [23]. Although all classical algorithms can also be performed on quantum computers, quantum algorithms usually use some of the basic features of quantum computing, such as quantum superposition or quantum entanglement. Problems that cannot be avoided with classical computers are still unsolvable with quantum computers [24]. Quantum algorithms can solve some problems faster than classical algorithms [25], because the quantum superposition and quantum entanglement used by quantum algorithms may not be effectively analogous to classical computers, so quantum computers can be used to solve some difficult problems that are not feasible on classical computers [26].

The following describes the algorithm steps of the above quantum algorithms.

(1) Shor's large number decomposition algorithm

Suppose we need to decompose N, then

i. Find a number α, which needs to be mutually identical with N, that is, to meet $gcd(\alpha, N)$=1. (The minimum common divisor is 1)
ii. Find a power exponent r, satisfying α^r =1(mod N) the most minor r. (Meaning, divided by N, α^r the most minor r corresponding to the remainder of 1)
iii. If r is even, then calculate $X=\alpha^{r/2}$(mod/ N). If $x+1\neq 0$(mod/ N), then $\{p,q\}=\{gcd(x+1,N),gcd(x\text{-}1,N)\}$, otherwise look for another α, repeat the above process until you find a α that meets the conditions.

The above algorithm requires constant attempts to α, which is very good at uncertain Turing machines because the uncertain Turing machine can look for exponential α at the same time, and such acceleration can cancel out the exponential complexity of the algorithm [27–31].

(2) HHL algorithm for solving systems of linear equations

After a certain format conversion of the linear equation system, it can be solved by the HHL algorithm, which mainly contains the following three major steps, and requires the use of a total of three registers of right-end term bits, storage bits, and auxiliary bits.

i. Construct the right-end term quantum state, perform phase estimation of the parameters including the left-end term matrix for the storage bits and right-end term bits, and transfer all the integer form eigenvalues of the left-end term matrix to the base vector of the storage bits.
ii. Perform a series of controlled rotations with eigenvalues, filter out all quantum states related to eigenvalues, and transfer eigenvalues from the base vector of stored bits to the amplitude.
iii. Inverse phase estimation of the feature storage bit and the right term bit, the eigenvalue on the amplitude of the storage bit is merged onto the right end term bit, and when the auxiliary bit is measured to obtain a specific state, the quantum state can be solved on the right term bit.

(3) Grover search algorithm

Suppose the search task has $N = 2^n$ eligible items, and each item is indexed by assigning an integer from 0 to $N-1$. Also, suppose there are M different valid inputs, that is, there are M inputs $f(x)$=1. In this way, the steps of the algorithm are as follows:

i. Start with registers of n qubits initialized in the state.
ii. By applying H to each qubit in the register, prepare to stack the registers evenly:

$$|register\rangle = \frac{1}{\sqrt{N}} \sum_{x=0}^{N-1} |x\rangle \tag{1}$$

iii. Apply the following operation $N_{optimal}$ times to the register:

Apply a phase black box of O_f with a conditional phase shift of -1 to the solution term.
Apply H to each qubit in the register.
The conditional phase shift -1 is applied to each computed. underlying state except $|0\rangle$. This can be represented by a single.
Operation $-O_0$, since O_0 only represents the conditional phase shift of the pair.
Apply H to each qubit in the register.

iv. Measure registers to get the index of an item with a high probability of being a solution.
v. Check if it is a valid solution. If not, start the operation again.

Fig. 3 is a schematic diagram of the Grover algorithm, representing the classical-quantum algorithm. Each of the lines represents a qubit, and the quantum gate operations are represented using different squares.

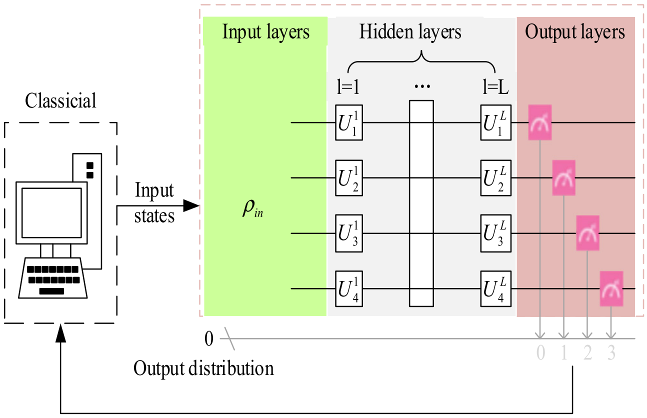

Fig. 4. General structure of the discrete variable quantum neural network.

(4) Quantum annealing algorithm

The quantum annealing algorithm mainly uses the mechanism of quantum fluctuations, that is, the quantum tunneling effect, to complete the optimization process. The steps of the quantum annealing algorithm are expressed as follows [32]:

i. According to the problem to be optimized, the evaluation function $H_q = H_{pot} + H_{kin}$ of the quantum system is constructed, that is, the quantum Hamiltonian function. Where H_{pot} is the potential energy, that is, the evaluation function in the simulated annealing algorithm, H_{kin} is the kinetic energy.
ii. Initialize each parameter, T_0 is the initial temperature of quantum annealing, the Γ is the lateral field strength, the changing lateral field strength causes a quantum transition between different quantum states, the maximum number of iterations is *Maxsteps*, the initialization state is *x*, and the corresponding state energy is $H_{pot}(x)$.
iii. Random perturbations produce a new state *x*' corresponding to the state energy $H_{pot}(x')$.
iv. Calculate the energy difference $\Delta H_{pot} = H_{pot}(x') - H_{pot}(x)$ and $\Delta H_q = H_q(x') - H_q(x)$, if $\Delta H_{pot} < 0$or $\Delta H_q < 0$, the system accepts the new solution *x* = *x*', and vice versa, if *exp*($\Delta H_q/\Gamma$)<*rangdom(0,1)*, then *x* = *x*', otherwise re-perform iii.
v. The temperature reduction operation is carried out, and the change of Γ is similar to the temperature Γ effect in the simulated deheating, and the lateral field strength change is in the form of $\Gamma = \Gamma - (\Gamma_0/Maxsteps)$.
vi. Determine whether the termination condition is met, if Γ=0 is met, the quantum annealing algorithm terminates, otherwise, repeat iii.

2.2. Applications of the quantum computing

Quantum computing, which combines computer science with quantum mechanics, is a rapidly growing research field [33–34]. The underlying power of quantum computing lies in the superposition and entanglement of states, allowing exponential computations to be performed in parallel [35–36]. Superposition and entanglement are very useful in computing and communication technologies. Due to these two quantum behaviors, specific problems that cannot be dealt with by classical computers can be effectively solved by quantum computers, such as the important role of quantum computing in power systems [37–38], the wide application of quantum computing in chemistry [39] and the application of quantum computing in neural networks [40]. This paper takes a quantum neural network as an example to briefly summarize the practical application of quantum computing.

A neural network is a mathematical model [41], an abstraction of the biological nervous system, consisting of adaptive units called neurons, which are connected by an extensive network of synapses [42]. The basic elements of a neural network are artificial neurons, which are mathematical abstractions of biological neurons [43]. When each neuron is activated, it releases neurotransmitters to the connected neurons and changes the electrical potential of those neurons. Each neuron has a threshold potential; When the potential exceeds the threshold, neurons are activated [44].

An artificial neural network is a group of neurons, some or all of which are connected in a pattern [45]. Notice that we put neurons on both the input and the output. These input and output neurons are not the ones described earlier but depend on the learning problem. There may or may not be activation functions associated with them [46].

Fig. 4 shows the general structure of a discrete variable quantum neural network. Similar to classical neural networks, deep quantum neural networks also have input, output, and L hidden layers. Classical computers send quantum states to the quantum neural network and sample the output distribution generated by the quantum neural network. Based on the resulting output, the parameters are updated until the desired output is achieved within the setup error.

The problems considered by the quantum neural network are similar to the process of a classical neural network, including giving quantum information tasks, data preparation, data embedding, training network, optimizing parameters, and finally obtaining the best probability [47]. To compute entanglement with quantum neural networks, the goal should be to detect and quantify a general measure of entanglement, regardless of whether the quantum state is discrete or continuous [48].

Fig. 5. Visual-evoked EEG experiments.

Taking discrete variable quantum neural network as an example, it is a quantum circuit of quantum perceptron, which is organized into unitary operations of the hidden layer, acting on the input quantum states and producing corresponding output quantum states. The network uses separate qubit registers to parameterize the input and output of the quantum circuit and defines the quantum neuron as a completely positive mapping between the two. It has been proved feasible to realize classical artificial neurons in quantum circuits [49–50], and the network thus obtained has universality and operability for quantum computing.

3. Brain-computer interface

BCI technology refers to a new human-computer interaction method that enables people to communicate with the external environment by outputting control signals through electronic devices such as computers without the participation of the peripheral nervous system and muscle tissue [51]. Its purpose is to establish a direct communication and control channel between the human brain and machine [52–53], to provide patients with diseases, people with disabilities, and healthy individuals with alternative ways to communicate and control the outside world, to improve or further enhance their quality of life. Fig. 5 shows subjects for visual evoked stimulation experiments using an EEG (EEG) cap. Accept the noise stimuli. In recent years, BCI has attracted more and more attention from academia and the public due to its many potential applications [54]. The following part mainly introduces the development of the brain-computer interface in recent years.

3.1. Traditional BCI

The history of BCI has evolved from early digital technology to today's highly complex methods for signal detection, recording, and analysis [55–56]. In the past decade, advances in brain science and computer technology have led to the exciting development of BCI, whose potential applications have attracted more and more attention from scholars and the public [57], thus making BCI a top research area in applied science. Traditional EEG-based BCI usually relies on only single signal input, a single sensory stimulus, or a single brain pattern. The single-mode BCI system has made great progress in paradigm design, algorithm, and application of brain signal processing.

BCI is a technology that converts signals generated by brain activity into control signals without the involvement of peripheral nerves and muscles and uses these signals to control external devices [58]. A BCI system consists of different continuous processes that in turn collect signals, extract desired features from tasks, select more relevant subsets from feature sets, classify mental states, and generate feedback signals. The extraction, decoding, and study of these brain signals are performed with the help of a variety of non-invasive monitoring techniques, such as EEG, functional magnetic resonance imaging, and functional near-infrared spectroscopy [59]. Table 2 describes the properties of some classifiers of EEG BCI [60].

The essence of these techniques is a low signal-to-noise ratio [63] because brain activity is often affected by environmental, physiological, and activity-specific noise from multiple sources, known as "artificial interference" [64–65]. In electroencephalography, measuring potentials on the scalp can reflect neuronal activity and can be used to study a variety of different brain processes, such as BCI. Because of the fast propagation speed of the electric field, EEG signals have good temporal resolution [66–67].

3.2. Hybrid BCIs

Traditional BCI systems have been facing two fundamental challenges: lack of high detection performance and control command problems. To this end, the researchers proposed a hybrid BCI to address these challenges. Table 3 shows the performance differences between traditional BCI and hybrid brain-computer interface (hBCI). This paper mainly discusses the research progress of hBCI and summarizes three types of hBCI, namely, hBCI based on a multi-brain model, multi-sensory hBCI, and hBCI based on multi-modal signals. By analyzing the general principles, paradigm design, experimental results, advantages, and applications of the latest hBCI system, we found that using hBCI technology can improve the detection performance of BCI and achieve multi-degree/multi-function control, which is significantly better than single-mode BCI [68].

Table 2
A classifier for EEG-BCI.

Name and type	Verification protocol	Complex processing power	Accuracy	Sensitivity	Reference
LSTM + Attention	Intr theme	The network consists of three layers. Each layer has seven cells	98.3 ± 0.9	95.9 ± 1.7	[61]
Deep Learning	Cross subject	Next comes the attention layer, followed by the fully connected layer with the S-type activation function. This makes the proposed network computationally powerful and expensive	83.2 ± 1.2	82.2 ± 2.1	
Channel Related	Intra theme	For feature extraction, they first found Pearson correlation coefficients, which were then used to estimate PSD	87.03	It is sensitive to the length of the sliding window and insensitive to the number of filters in the classifier	[62]
CNN classification	Cross effect	Next comes a CNN model with two one-dimensional convolution layers, where the size of the filter is the same as the number of electrodes. The CNN given here is slightly less complicated and faster	83.93±9.21	Nothing can stop this sensitivity	

Table 3
The difference between traditional BCI and hybrid BCI.

Traditional BCI	The traditional Brain-Computer Interface has many shortcomings. For example, BCI based on motor imagination requires subjects to do a lot of exercises. BCI based on P300 bit requires repeated scintillation. The number of control commands on Steady-state visual evoked potential-based BCI is affected by stimulus frequency and other factors	[55–62]
Hybrid BCI	Using hBCI technology can improve the classification accuracy of BCI and increase the number of control commands, which is better than single-mode BCI	[68–73]

Based on the above questions, in the following content, we briefly describe the application of hybrid BCI technology by researchers.

We already know that different options need to be considered when dealing with HDL-based BCI. In particular, the methods used to detect mental tasks need to be carefully selected. Portable and non-invasive methods such as electroencephalography, magnetoencephalography, or functional magnetic resonance imaging should be preferred. Therefore, BCI can provide communication and control options for patients with neuromuscular diseases [69]. At present, the EEG signal is the most popular method to implement the BCI system in practical application due to its non-invasive, easy to operate, and relatively cheap cost [70]. A variety of EEG-based BCI applications have been developed to facilitate the daily life of severely disabled people [71–72]. To take just a few recent reports, in 2020, the Johns Hopkins University School of Medicine and its Applied Physics Laboratory, APL researchers enabled quadriplegics to control two robotic arms at the same time using their "mind" to pick up a knife and fork and cut a cake, and then deliver the cake to their mouth [73]. One promising type of such application is EEG-based brain-controlled wheelchairs, which could help disabled people, helping them move voluntarily and potentially improving their quality of life.

Fig. 6 shows a sample of S1′s path to each target (left) and corresponding commands (right) in an experimental experiment. The subjects performed several appropriate mental tasks to navigate the wheelchair to its destination. Subjects did not perform any mental tasks during the action and stop periods [74].

3.3. Intelligent applications of BCIs

As mentioned above, BCI has experienced nearly half a century of development, and although it has been well known among the public, the application of BCI in practical scenarios is still very limited [75]. Neither traditional nor hybrid BCI is meant to be intelligent BCI. At present, BCI is not intelligent or even clumsy, which does not match BCI users, greatly reducing the effectiveness of users' control of BCI, and seriously affecting BCI users' experience and satisfaction [76]. Therefore, the intellectualization of the BCI system is an inevitable requirement of BCI human factor engineering. Based on the above considerations, it is necessary to introduce appropriate new AI technologies into the BCI system, endow the BCI system with a certain degree of intelligence, and expect to enhance its usability of the BCI system.

Fig. 7 shows the relationship between BCI and AI. Fig. 7a shows the parallel development of BCI and AI, which is an early relationship between the two. Fig. 7b shows the overlapping development stages of BCI and AI, in which BCI and AI are responsible for two functions, independent of each other and cooperating [77–78]. Fig. 7c shows the introduction of AI into BCI. The typical application is the introduction of machine learning algorithms such as deep learning into the BCI system. Fig. 7d shows the introduction of BCI into AI, typically using BCI as an input channel for an AI system [79–80]. With the further development of BCI and AI, the two cross and merge, and the intelligence of BCI can be enhanced through AI. An intelligent BCI system should be able to intelligently perceive BCI user status and peripheral environment information and can understand and integrate this information, and then judge and reason.

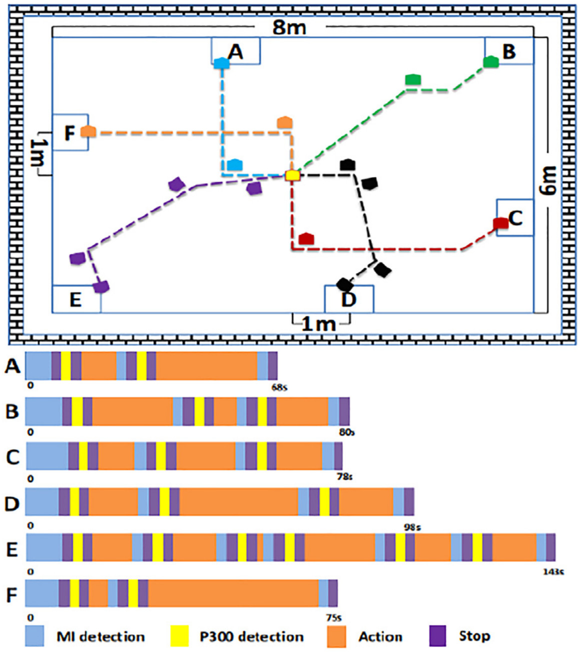

Fig. 6. The experimental sample.

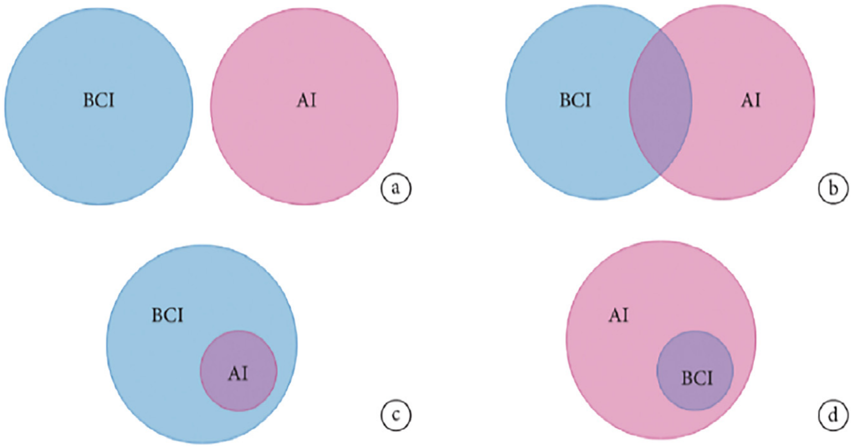

Fig. 7. Diagram of the relationship between BCI and AI.

4. Hybrid application of the quantum computing and the brain-computer interface

In recent years, the application of quantum computing in other fields has been paid more and more attention by the country and researchers. By constructing proper quantum algorithms, researchers can solve certain computationally difficult problems, such as large number decomposition and complex path search, that are almost impossible for classical computers, in acceptable time [81–83]. The solution to these problems will have a profound impact on information fields such as cryptography [84], big data, machine learning [85], and artificial intelligence [86–91]. For example, the application of quantum computing in artificial intelligence [92]. On the one hand, a large number of tools and ideas of artificial intelligence can be used to solve complex quantum problems. On the other hand, quantum computing may also offer unprecedented opportunities to improve, accelerate or innovate AI. The following part mainly describes the mixed application of quantum computing and the brain-computer interface.

BCI and quantum computers are undoubtedly cutting-edge technologies that appeared simultaneously in history. Brain-computer interface is the core technology of a new generation of human-computer interaction and human-computer hybrid intelligence, and it is also a milestone of technology to change the course of life. At the same time, the brain-computer interface is the connection path and control channel established between the human brain and computer or other equipment, which can receive signals through the computer. The human brain can directly express ideas or control other equipment, get rid of the dependence on external nerves

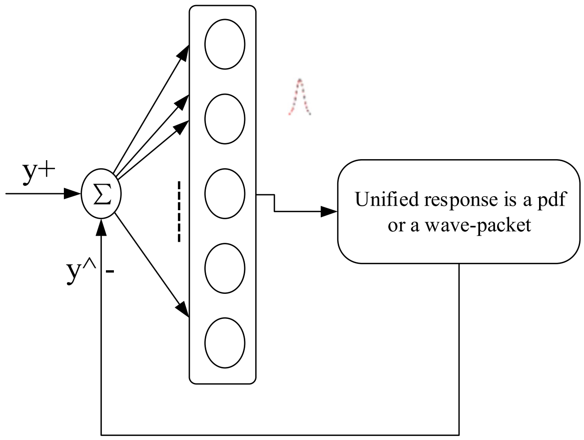

Fig. 8. Conceptual framework of the RQNN model.

and muscles, and truly realize the control of equipment with the "mind" and liberate limbs. However, since the rapid development of quantum computing and brain-computer interface, the hybrid application of the two is relatively less than in other fields [93–97], Two typical examples are presented below.

4.1. Recursive quantum neural networks

Literature [98] describes a neural information processing structure inspired by quantum mechanics and combined with the Schrodinger wave equation. The structure, called a recursive quantum neural network (RQNN), can describe non-stationary random signals as time-varying wave packets. A robust unsupervised learning algorithm enables RQNN to effectively capture the statistical behavior of input signals and estimate the signals embedded in noise with unknown characteristics. The RQNN filtering program is applied to a brain-computer interface based on two types of motion images. Its goal is to filter EEG signals before feature extraction and classification to increase signal separability. A two-step inside and outside quintuple cross-validation method is used to select algorithm parameters for topics - specifically 9 topics. Studies have shown that in multiple sessions, subject-specific RQNN EEG filtering significantly improves brain-computer interface performance compared to raw EEG or Savitzky-Golay filtering EEG alone [99].

BCI technology is a means of communication that allows individuals with severe movement disorders to communicate with external assistive devices through EEG or other brain signals. Recently, in conjunction with the feature extraction phase, researchers studied spatial filtering algorithms based on the Kullback-Leibler [100] common spatial pattern [101] and Bayesian learning to interpret EEG with very low signal-to-noise ratios [102–103]. Coyle et al. [104] extensive research on spatial filtering methods based on Bayesian learning and the use of publicly available EEG data are reported. Neural networks and self-organizing fuzzy neural networks have also been used to improve the divisibility of motion imaginary bbcis signals [105–106]. In this paper, under the framework of the recursive quantum neural network, quantum mechanics (QM) and neural network theory are used to preprocess EEG signals.

EEG signals can be considered as a random or random process implementation [107]. When the exact description of the system is not available, a random filter can be designed according to the probability measure. Bucy pointed out in [108] that each solution to the stochastic filtering problem involves the calculation of the time-varying probability density function (PDF) over the state space of the observing system. The architecture of the RQNN model is based on the QM principle, and the Schrodinger wave equation (SWE) [109] plays a major role. The method can estimate the time-varying PDF online, which can estimate and remove the noise in the original EEG signal.

In quantum terms, ψ represents the state, which is called the wave function or probability amplitude function. The time evolution of the state vector is expressed by ψ

$$ih\frac{\partial\psi(x,t)}{\partial t} = H\psi(x,t) \tag{2}$$

This is the Hamiltonian or energy operator and gives (∂/∂t) where 2(i.e., h) is the Plank constant [110]. This is the wave function associated with quantum objects at the point (x, t) in space-time.

Fig. 8 shows the basic structure of the RQNN model, in which each neuron modulates the space-time field through a unified Gaussian form of quantum activation function that aggregates information from the observed noise input signal. Thus, the solution of SWE gives the activation function. From a mathematical point of view, the time-varying one-dimensional nonlinear plane is a partial differential equation describing the dynamic wave packet (PDF's modular square wave) in the presence of a potential field (or function) of a force field (particle wave function defined by forced movement) [111].

Through experiments, researchers found that for Direct Current signals with three different noise levels, the filtering effect of RQNN was significantly better than the Kalman filter [112]. The learning structure of RQNN and the related unsupervised learning algorithm is improved to consider the complexity of the EEG signal. The basic approach is to ensure that the statistical behavior of the input signal is appropriately transmitted to the wave packet associated with the quantum dynamic response of the network [113].

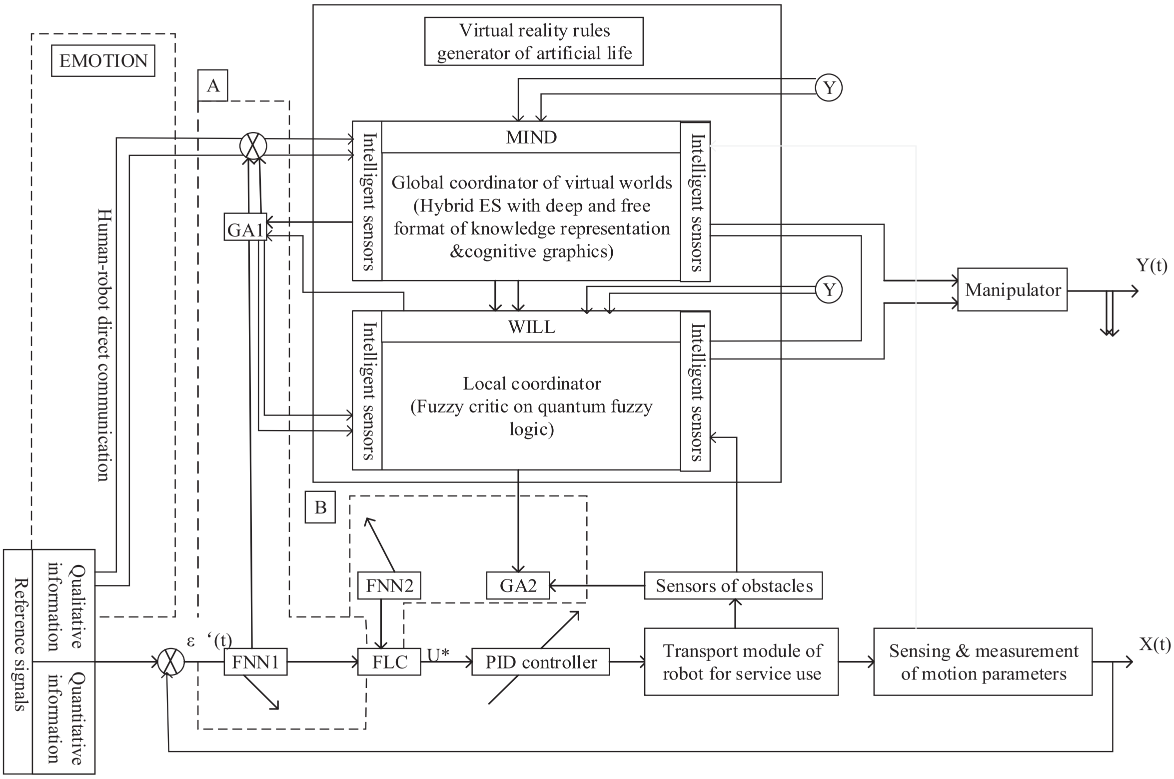

Fig. 9. Structure of an AI control system with distributed knowledge representation.

4.2. Intelligent control system based on quantum soft computing

The literature [114] describes a new approach to the design of intelligent control systems using quantum soft computing techniques. Development of a new form of direct human-machine communication (including emotion, instinct, and intuition) and autonomous motion control systems (Fig. 9).

With the popularity of smartphones, BCI needed more advanced technology which led to the development of this technology [115]. The brain is one of the most complex systems known, and it requires us to study it in depth. Existing projects such as whole-brain simulations use techniques like supercomputing to enable massively parallel cortical column simulations. However, as social technology continues to evolve, what is needed is a platform that is more scalable than supercomputing (e.g., quantum computing) and can give us a better understanding of the complexity of the brain [116]. The chemical transformation processes that occur in the brain are as necessary as the processes represented by the principles of quantum mechanics and the similar computing environments that represent them. The benefit of quantum computers is that they can store and process local information about simulated quantum systems, thus providing great scalability [117].

Soft computing techniques are based on genetic algorithms, fuzzy neural networks, and fuzzy logic reasoning. Quantum computing intelligence employs quantum genetic search algorithms and quantum neural networks. These algorithms consist of three main operators. In the selection of genetic algorithms, crossover and variation operators are used; Superposition, entanglement, and interference are applied in quantum search algorithms.

Three subsystems are described in [118–119] that organize systems of service robots to enable autonomous navigation and these calculations. The motion control system consists of four functions: motion control, work planning, learning, and recognition. These three subsystems are based on fuzzy control, fuzzy neural networks, and genetic algorithms. Experimental results on the development of robots show that the proposed method is very useful for the autonomous motion control of robots.

5. Existing problems and future directions

In the current society, the hybrid application of quantum computing and brain-computer interface has developed rapidly, but from the specific examples, there are still not many studies in this area, the time of social application is very long, and some decisive problems need to be further studied.

With the continuous development of quantum computing, quantum computers are expected to become the next generation of information processors, and once implemented, they will hopefully bring us more powerful computing power than existing classical computers. However, in terms of comparison and development positioning with classical computing, quantum computing currently only has theoretical advantages in some problems that classical computing cannot or are difficult to solve, has not been fully proven, and is not superior to classical computing in solving all problems. In addition, the complex manipulation of quantum computers still requires classical computer assistance, and for a long time to come, quantum computing will not be able to completely replace classical computing, and the two will run side by side and complement each other for a long time.

In the brain-computer system, on one side is the brain, and on the other side is the machine, the brain changes the state of the machine, and controls the external device to achieve a certain action. The machine is also trying to change the state of the brain, that is, based on the observed plasticity of the cerebral cortex, as long as a certain amount of information or training can be given to change the way the neural network of the cerebral cortex is connected, which can be used to slow the damage of diseases in the future, or used in healthy people to improve people's cognitive ability. However, despite the many achievements of brain-computer interfaces, they are still basically at the level of laboratory demonstration so far, and there is still a long way to go before they are truly commercial applications. The challenges of brain-computer interfaces are very many. From the perspective of basic research, a lot of things related to brain science have not yet been settled; From an engineering point of view, there are still many problems to be solved about how to interpret signals; From the perspective of popularization and application, brain-computer interfaces involve complex ethical issues, which are the challenges that brain-computer interfaces will encounter in the development process.

However, after several key technological breakthroughs at this stage, the research community has published a variety of research reports on brain-computer interfaces, and the development of brain-computer interfaces has shown exponential growth. Some so-called black technology companies continue to speak out and publish their research results on brain-computer interfaces, which seems to indicate that brain-computer interfaces will usher in a new stage of development shortly.

Through the above analysis of the two aspects of quantum computing and brain-computer interface, we will find that the research on the combination of quantum computing and brain-computer interface is difficult because of the complexity of quantum computing and the limitations of brain-computer interface, but with the continuous development of quantum computing and brain-computer interface, the mixed application of the two will become a reality, in addition, the combination of quantum computing and other intelligent technologies will also become a hot spot in future research.

6. Conclusions

This paper reviews the progress of hybrid applications of quantum computing and brain-computer interfaces. This paper mainly summarizes the current research situation of quantum computing and some quantum algorithms, the classification and intelligent applications of BCI, and the comprehensive application of quantum and BCI. This paper introduces the four classical algorithms of quantum computing and their advantages and disadvantages, the two types and advantages and disadvantages of brain-computer interfaces, and the specific application of quantum computing and brain-computer interfaces in the current social background.

So far, various intelligent technologies have gradually combined quantum and brain-computer interfaces, such as automatic navigation systems and intelligent robots have been combined with BCI. In addition, although the road to building a practical universal quantum computer is winding, we believe that with the efforts of many scientists and mechanical engineers to explore the field of quantum information, it will eventually be achieved. In the past two years, researchers have not only made greater progress in quantum research but also gradually linked quantum computing with brain-computer interface, brain science, and brain-like intelligence. We believe that scientists in the future will make significant progress in this area.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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