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Edge cognitive computing based smart healthcare system

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HIGHLIGHTS

- We present a ECC-based smart healthcare system.
- We describe the dynamic resource allocation mechanism.
- Experimental results show that the system realizes optimization of resources.

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ABSTRACT

With the rapid development of medical and computer technologies, the healthcare system has seen a surge of interest from both the academia and industry. However, most healthcare systems fail to consider the emergency situations of patients, and are unable to provide a personalized resource service for special users. To address this issue, in this paper, we propose the Edge-Cognitive-Computing-based (ECC-based) smart-healthcare system. This system is able to monitor and analyze the physical health of users using cognitive computing. It also adjusts the computing resource allocation of the whole edge computing network comprehensively according to the health-risk grade of each user. The experiments show that the ECC-based healthcare system provides a better user experience and optimizes the computing resources reasonably, as well as significantly improving in the survival rates of patients in a sudden emergency.

1. Introduction

The economic development and environmental changes in human society have raised the morbidity of the chronic diseases, so that they now represent the greatest threat to human health [1]. The traditional healthcare systems can be divided into three layers, i.e., the collection layer, the transmission layer and the analysis layer. In the collection layer, the sensor in the body area network (BAN) [2,3] collects the sensing data as per the specified frequency, sends it to the gateway node or base station (BS) through the intelligent terminal or smart phone [4,5]. Then, the gateway or BS sends it to the analysis layer (such as a cloud data center) through the internet, and the data is stored and analyzed in the cloud data center utilizing machine learning and data mining algorithms. Finally, the system obtains the health status of the users, and takes the corresponding medical treatment measures [6].

Although the healthcare system has brought convenience to patients, there are the following problems:

- Due to the multi-modality of the medical data, the traditional machine learning and data mining methods fail to accurately discover the hidden value in the data [7]. Thus, a more intelligent method is required for a comprehensive disease analysis for all types of data.
- BAN sensors send the health data to the cloud for the processing, which increases the communication latency, and fails to provide a prompt medical analysis and service in emergency situations [8,9].
- The inflexible network resource deployment leads to a waste of resources. Moreover, it fails to provide a personalized resource service for users by their different health statuses.

To overcome these problems, lots of relevant researches have been studied. For example, in reference [10] authors novelly proposed a multi-tier application-level architecture named BodyCloud that enables the real-time monitoring and analysis of cardiac data streams of many individuals in a broad range of application domains, such as healthcare, emergency management, fitness and behavior surveillance. And reference [11] introduced state-of-the-art of Cloud-assisted BAN architectures for many human-centered application domains such as healthcare, sport, fitness. Moreover,

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cognitive computing can be exploited by the medical professionals [12]. It offers a diagnosis through the medical cognitive system, finds an optimal decision from all types of data and content, and then takes the appropriate actions [13]. In the medical industry, the risk of missing the correct data relation and pattern is very high. If important information is ignored or misunderstood, patients will suffer from long-term harm and even death. Cognitive computing, as a multi-disciplinary subject integrated by technologies such as machine learning, artificial intelligence, and natural language processing [14], is able to find the disease pattern and the relationship from the data [15], comprehensively analyzes all the different data points, and accordingly help the medical professionals to learn and find the correct solutions [16,17]. In a cognitive system, the cooperation between the human and the machine is inherent, which enables medical institutions to gain more value from the data and solve complex problems [6,18–21].

Furthermore, recent advances in edge computing will have profound impacts on healthcare system [22]. Edge computing deploys computing resources closer to end devices, which can efficiently improve the quality of service (QoS) for applications that require intensive computations and low latency [23]. However, the cognitive computing and edge computing are still divided [24].

To solve the above problems and fully combine the various advantages of cognitive computing and edge computing, in this paper, we propose a Edge-Cognitive-Computing-based (ECC-based) smart healthcare system. This system can monitor and analyze the physical health of users with cognitive computing. Moreover, the proposed system obtains the corresponding health risk grade of the user under different health statuses in reference to a health risk assessment table, further adjusts the computing resource distribution of the whole edge computing network comprehensively pursuant to the health risk grade of each user, and enables the network to have a user-oriented deeper application-aware cognitive intelligence [25]. The main contributions of this study are as follows.

1. We present a ECC-based smart healthcare system based on data and resource cognition, and describe the key technology used for building the healthcare system.
2. We describe the dynamic resource allocation mechanism based on the user's health status, and solve the resource allocation and switching problems of the edge cloud based on the user's physical health cognition.
3. We introduce details of the design and implementation of the ECC-based healthcare system, and build a test platform. The experimental results show that the system realizes optimization of the resources.

The remainder of this paper is organized as follows. Section 2 introduces the ECC-based health system architecture. Next, some key technologies at different levels will be given in Section 3. Then, Section 4 presents the test platform of the ECC applied in the healthcare field, and describes the healthcare scenario and introduces details of the design and implementation of the healthcare system. Finally, Section 5 concludes the paper.

2. ECC-based smart healthcare system architecture

2.1. Motivation

To realize an intelligent and real-time healthcare system, it is necessary to deploy the definite cognitive computing capability in the network edge, and carry out a cognitive analysis of the user's physical health data and network resources. This effectively reduces the latency and provides more communication resources for users in an emergency condition, and also ensures reliable and the latest patient information to the doctor.

Fig. 1 illustrates an ECC-based smart healthcare system. It includes two application scenarios, i.e., the normal case and the emergency case. In the normal case, User 1 is connected to the edge node Edge1, while Users 2, 3 and 4 are connected to the Edge2 node. In the emergency case, User4 suffers from a heart attack. The system recognizes the situation, and then, redistributes the resources and distributes Users 1, 2 and 3 to Edge1, while Edge2 independently serves User 4. Thus, User 4 can receive sufficient medical service.

The ECC-based smart healthcare system leverages data cognition and resource cognition, providing high energy efficiency, low cost, and high user Quality of Experience (QoE). We will introduce the ECC-based smart healthcare in detail, which includes the ECC-based smart healthcare engine and the ECC-based smart healthcare data flow type.

2.2. ECC-based smart healthcare system engine

In this subsection, we first investigate the functionality of the data cognitive engine and the resource cognitive engine, and then introduce their co-fusion and interaction.

- **Data cognitive engine:** This engine collects the external data from the cognitive application which include physical signal and user behavior. Moreover, the data cognitive engine collects the internal data, including the network type, service data flow, communication quality, and other dynamic environmental parameters from the resource network environment. In addition, it carries out the comprehensive big data analysis through machine and deep learning, involving cognition to external data and internal data, and realizes the environmental perception and human cognition to meet the requirements of various applications. For instance, considering the mobility of single user through cognition to user's behavior, edge computing environment is capable of realizing the real-time service switching, providing continuous computing service for users and enhancing the user QoE. When considering multi-user resource allocation under a resource-competitive environment, the user with the highest priority level will be provided with the best network resources. For instance, cognitive health surveillance utilizes the static basic information about users and the disease risk level information updated by the users in real time, and then combines the dynamic network resource information in the edge computing environment. It then provides the maximum edge computing resources to the user with the highest disease risk, and improves the treatment probability of patients.
- **Resource cognitive engine:** This engine leverages the cognitive computing to learn the edge cloud computing resources, communication resources, and the network resources. Then, it sends the integrated resource data to the data cognitive engine in real time. Moreover, it can receive the analysis result of the data cognitive engine and realize a real-time dynamic resource allocation and optimization. In addition, it can take advantage of the network softwarization technologies, including the network function virtualization (NFV), software-defined network (SDN), self-organized network (SON), and network slicing, and offer high reliability, high flexibility, ultra-low latency, and extendibility of the edge cognitive system. Moreover, it utilizes the cloud platform and intelligent algorithms to form the cognitive engine with resource optimization and energy saving, in order to enhance the user QoE and meet the different demands of various heterogeneous applications.

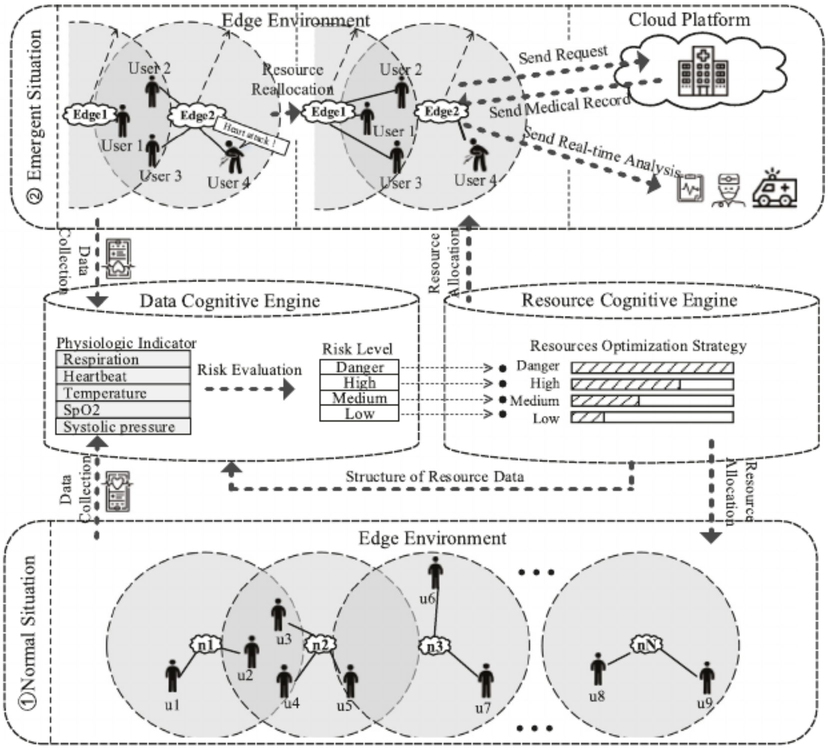


Fig. 1. ECC-based smart healthcare system.

2.3. ECC-based healthcare system data flow

- **External data:** The data source in the application scenario provides unprocessed external data, including physical signs and user static information under the cognitive health surveillance, and daily behavioral habits information about the mobile user. The external data is referred to and analyzed by the data cognitive engine. By using the data cognitive engine through the data analysis and processing, e.g., machine learning and deep learning, the external data flow yields the dynamic change of the internal data flow. Meanwhile, it guides the resource cognitive engine to make an optimal distribution of the resources.
- **Internal data:** The real-time data flow in dynamic network environment contains various resources, including the edge cloud computing resources, environmental communication resources, network resources (e.g., network type, service data flow, communication quality, and other dynamic environmental parameters), and dynamic real-time user information (e.g., real-time disease risk level of the user under the cognitive health surveillance, and real-time behavior action information about the mobile user). The internal data dynamically guides the network resource distribution and is continuously updated in real time to form a closed data flow circulation.

3. Key technologies for ECC-based smart healthcare system

The resource cognitive engine provides resource cognition of the edge environment, as well as achieving ultra-low latency, the ultra-high reliability, and energy efficiency of the system. The data cognitive engine is able to cognize the big data, and then performs the intelligent healthcare. The key technologies in the data and resource cognitive engine and the healthcare application can be represented as follows.

3.1. Key technologies deployed in the data cognitive engine

Machine Learning: It can be used to realize the cognitive intelligence as required for the cognitive system. The solution with method of data-driven and modeled with supervised learning or unsupervised learning enables the system to have definite cognitive intelligence. The common machine learning methods include regression analysis, decision tree, Bayesian network, correlation analysis, clustering analysis, dimension reduction, and artificial neural network.

Deep Learning: This simulates the cognitive process of people to the external environment well in the visual and auditory senses. Deep learning should be based on the mass data. The data level directly influences the accuracy of the learning algorithm. At the same time, the deep learning has good effect in terms of the visualization, natural language processing, and multimedia data processing.

Cognitive Computing: This represents a brand new computing mode, and includes an information analysis, natural language processing, and a large number of technological innovations in the machine learning field, to assist the decision makers in gaining an extraordinary insight based on the massive amounts of unstructured data. Cognitive computing carries out data cognition for the information relevant to the user's disease, and resource cognition with respect to the information about the network and the computing resource environment of the user. These two cognitions supplement each other, providing a personalized service with an intelligence argumentation.

3.2. Key technologies deployed in the resource cognitive engine

Network Softwarization Technologies: The network softwarization technologies are formed by NFV, SDN, SON, and network slice, to realize the high reliability, high flexibility, ultra-low latency, and extendibility of the edge cognitive system. The SDN can flexibly design the network as per the user's demands, by separating the control and data layers, centralized management dispatching, and an open programmable interface. The network slice is to utilize the virtualization technology, and virtualize the physical infrastructure resource of the 5G network into multiple, mutually independent and parallel virtual network slices in accordance with the scenario's demands. Each network slice carries out a customized tailoring of the network function, and the arrangement management of the corresponding network resources in accordance with the service scenario demands and the service model.

Resource Management Technologies: These technologies build the cognitive engine with the resource optimization and the energy saving. They include the computing unload, handover strategy, caching and delivery, and the intelligent algorithms. The computing unload investigates the computing task assignment issue, distributes the computing resources in the edge cloud or the remote cloud reasonably. The handover strategy considers the issue of user mobility, and considers how to provide a seamless resource connection. Caching and delivering are used to arrange the predictive contents on the edge in advance, to gain the lower latency and reduce the core network load [26]. Intelligent algorithms conduct a reasonable resource optimization in accordance with the disease risk level of the users and the resource environment.

The resource cognitive engine based on the cloud platform exhibits mass storage and powerful computing functions. In addition, various branches of the data cognitive engine can be deployed in accordance with various medical demands. The problems that resource cognitive engine needs to solve include the classification of the cognitive engine, the functional design of the cognitive engine, the modeling of the cognitive algorithm, and the interface design of the cognitive engine.

4. System design and implementation

This section evaluates the performance of the proposed ECC-based smart healthcare system. We first create the test platform, mainly by considering the multi-user resource allocation problem in the healthcare scenario, and then investigate the performance with the medical cognition as the experimental scenario. Specifically, the healthcare community is shared with several patients that have a chronic disease. As a result, the problem is to specify the priority in the case of the network and computing resource shortage. A conventional network considers only the switching problem of the edge cloud resources for each user, rather than considering the differentiated service for the disease outbreak of the groups with a chronic disease, i.e., while communicating in peak hours in the case of an emergency, the patient suffers from a sudden disease, and reasonable resources cannot be distributed for the special situation of the patient. The insufficient communication resources will increase the latency, and the medical staff will fail to come on time, leading to a delay in the rescue.

4.1. Healthcare scenarios

In the medical cognition scenario, each individual user of smart clothing is required to meet a seamless connection to achieve the best user experience while moving. Moreover, each individual user should consider the best distribution of the overall medical analysis resources in accordance with the physical health conditions of the user in a multi-user community. In this paper we will describe the application scenario for the optimal distribution of resources in a multi-user community in detail.

Our ECC-based smart healthcare system will be introduced below in aspects of the user side, the edge side and the cloud platform.

- User side (data-collection layer): The user side is composed of the user, the smart clothing [27] and a mobile phone. The smart clothing collects the real-time physiological data of the user. The physical signs of the user include the electrocardiography (ECG), electromyography (EMG), heartbeat, temperature, and blood oxygen saturation (SpO2). The physiological data of the user is uploaded to the nearby edge computing node after it is collected by the smart clothing. Meanwhile, the mobile phone receives the result of the health analysis from the edge computing node [28].
- Edge computing side (computing-analysis layer): The mobile edge computing network is composed of the computing devices of the user community [29]. The edge computing node processes and analyzes the health data of the users, and distributes different computing resources to the users with different health levels. In the emergency case of the user, it sends an alarm to the hospital, receives the complete user data of the cloud platform, and carries out a comprehensive and accurate remote real-time medical diagnosis.
- Cloud platform side (storage-management layer): The cloud platform is operated and managed by the hospital. The cloud platform stores the basic information and the medical information, including the medical history of the user, e.g., the age, number of underlying diseases, and the nature of the disease. In an emergency case for the user, the cloud platform calls up all the information about the user, and transmits this information to the edge computing node for the analysis.

4.2. System design

It can be seen from Fig. 1 that in an emergency situation User 4 suffers from a heart attack, and the edge node 2 distributes all the computing resources to User 4, and transfers the other users of User2 and User3 to the edge node 1, to realize a dynamic resource distribution. Next, we design and implement the ECC-based healthcare system. The details of the system are as follows.

4.2.1. Interactive process of the cognitive engine and the user side

Fig. 1 shows that the user-side data is uploaded to the data cognitive engine. The data cognitive engine presents the disease risk assessment and gives the priority. According to the basic information, medical history, and real-time physiological data of the user, we divide the health risk level of the user into four levels, i.e., low, medium, high and danger. The adopted indexes include age, nature of disease, number of the underlying diseases, respiration, heartbeat, temperature, SpO2, and systolic pressure. Table 1 lists the risk assessment reference. The data cognitive engine carries out the comprehensive big data analysis through machine and deep learning on these physiological data of users, and transmits the analysis result to the resource cognitive engine, while the resource cognitive engine carries out the resource distribution in accordance with the optimal distribution strategy, and feeds back the resource data to the data cognitive engine. Through the static basic information of the users and the disease risk level information updated by the users in real time, it then combines the dynamic network resource information in the mobile edge computing environment, and provides the maximum edge computing resources for the user with the highest disease risk factors. The edge computing environment receives the distribution command of the resource cognitive engine, and carries out the resource redistribution of the user side.

Table 1
Risk evaluation reference.

Risk evaluation		Low		Medium	High	Danger
Basic information and medical record	Age (year)	–	[61-70]	[71-84]	≥85	–
	Nature of disease	Recovery	Chronic	Acute	Acute	–
	Numbers of underlying disease	0	1	2	3	–
Physiologic indicator	Respiration rate (/min)	[12-20]	[21-25] or [10-11]	[26-35]	[36-50] or [6-9]	>50 or ≤5
	Heartbeat (/min)	[60-90]	[91-100] or [51-59]	[101-140] or [41-50]	[141-160] or [30-40]	>160 or <30
	Temperature (°C)	[36.0-37.0]	[37.1-37.5] or [35.5-35.9]	[37.6-38.9] or [35.0-35.5]	[39.0-39.9] or <35.0	≥40.0
	SpO2 (%)	≥95	[90-94]	[85-90]	[80-85]	<80
	Systolic pressure (mmHg)	[89-139]	[140-159]	[160-179] or [85-89]	[180-189] or [80-84]	≥190 or <80

Table 2
Overview of the command set.

Command	Functionality	Applicability
UserInitiation ()	Initiate smart clothing application and collect user's physiologic indicators	User
Connect ()	Connect the optimal edge node nearby and return the IP address of the edge node	User
DataUpload (IP)	Upload the user's physiologic indicators to the edge node and update periodically	User
ResultDownload (IP)	Download the users' analysis result from the edge node and periodically update the data	User
Disconnect (IP)	Disconnect from the current edge node	User
EdgeNodeInitiation ()	Initiate the edge node and accept connection request from the user	Edge Node
DataReceive (User_ID)	Receive the user's physiologic indicators from connected users and periodically update them	Edge Node
RiskEvaluation (UserData)	Compute the user's current health risk according to medical information and physiologic indicators	Edge Node
ResourceAllocation (Risk)	Allocate proportional computing resources to the connected users based on the risk evaluation	Edge Node
SendingResult (User_ID)	Send health analysis result to the user and update periodically	Edge Node
DataCollection (CloudUser_ID)	Collect the user's basic information and medical history from the cloud	Edge Node
EmergencyTrigger (User_ID,Risk)	Connect to the hospital system, and conduct a comprehensive medical analysis for the high-risk user	Edge Node
UserHandover (User_ID)	Handover low-risk users to other edge nodes	Edge Node
DataTransfer (User_ID)	Transfer the users' basic information and medical history to the edge node	Cloud

4.2.2. Dynamic resource distribution mechanism

1. *User command set*

We designed the edge computing resource distribution workflow under multi-user conditions as follows. (1) User Initiation: The user initializes the smart clothing application and collects the physiological data. (2) Connecting and Data Uploading: The user connects to the nearby optimal edge node, meanwhile the physiological data is uploaded and there is periodic updating of the data. (3) Risk Evaluation and Resource Allocation: Compute the current disease risk level of the user according to the physiological data and other disease-related information, and distribute the appropriate computing resources to the user based on the evaluated risk level. (4) Sending the Result: Send the health analysis result to the user. (5) User Handover and Connection: When considering a user with a high disease risk, the low-risk user is handed over to the surrounding other edge computing node and connected to the other edge node. (6) Emergency Trigger, Data Collection and Transmission: Connect to the hospital system, collect the basic data and the historical medical data of the user from the cloud, transmit them to the edge node, and carry out a comprehensive and accurate medical diagnosis. Table 2 lists the designed command set.

2. *The flowchart of user and edge nodes*

We next design the flowchart from two different perspectives, the user side and the edge computing node. Fig. 2 shows the flowchart of the user side. The user first initializes the smart clothing application, connects to the edge node, collects the user data, and then offloads the data to the edge node. The user receives the analysis result feedback from the edge node. In the case of the resource shortage and low demand priority of the user, the user redistributes and connects to the other edge node. In other cases, the user collects the user data and continuously uploads the data.

The edge computing node first accepts the connection request, receives the user data, and then carries out the health risk level assessment based on the basic information, medical history, and real-time physiological data of the user. If the risk level is not high, the edge node will distribute the computing resources to the connected user and send back the analysis result to the user. Otherwise, if the risk level is high, the edge node hands over the low-risk users to other edge nodes, sends an alarm to the hospital, calls the user information from the cloud, and carries out a comprehensive and accurate medical diagnosis. Fig. 3 shows the flowchart of the edge node.

3. *Typical flow scenario*

In the ECC medical application scenario, the primary purpose is to optimize the resource distribution of the user based on the real-time health status of the user. Next, we provide more medical analysis resources for the critically ill users, reduce the rescue latency of the critically ill users, and enhance the survival rate of the patients with acute diseases. Therefore, we propose the following scenario. Two smart-clothing users, A and B, both connect to the nearest edge computing node B at some time. The smart-clothing user B suddenly suffers from an acute disease, and needs a large amount of medical analysis resources. Before the arrival of the ambulance, considerable analysis and diagnosis work can be finished. Thus, the edge computing node B hands over the user A in the "Low" or "Medium" level to the surrounding other edge computing node A, sends an alarm to the hospital, calls all basic personal information, medical history and other information about the user B from the cloud, and carries out a comprehensive and accurate medical diagnosis. Fig. 4 shows a flow diagram for the whole scenario.

4.3. Testbed and performance evaluation

1. *Testbed*

We design and implement a prototype system. We simulate the situation that the edge node B transfers the user A to the new edge node in the test platform. Fig. 5 illustrates the implementation testbed. The left-hand side of the figure describes the basic workflow for re-allocating the resources of the healthcare system, while its right-hand side shows the interface of the Android platform and the basic implemented functions, including acquiring the connection status, showing the Wi-Fi configuration, connecting to the appropriate edge node, searching for the computing node, and sending the message.

2. *Performance analysis*

To evaluate the performance of the proposed ECC-based healthcare system, we focus on the resource utilization rate of the edge environmental system. To quantify the user experience, we should

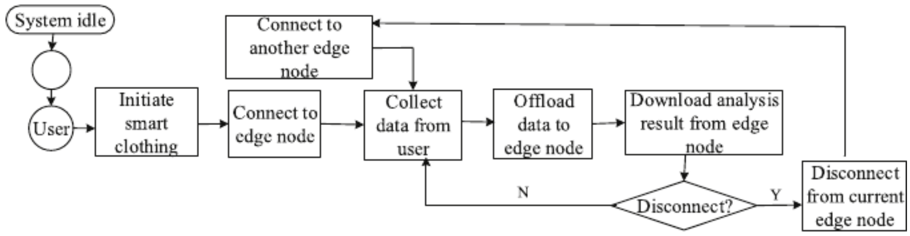


Fig. 2. The flowchart for users to offload and download data.

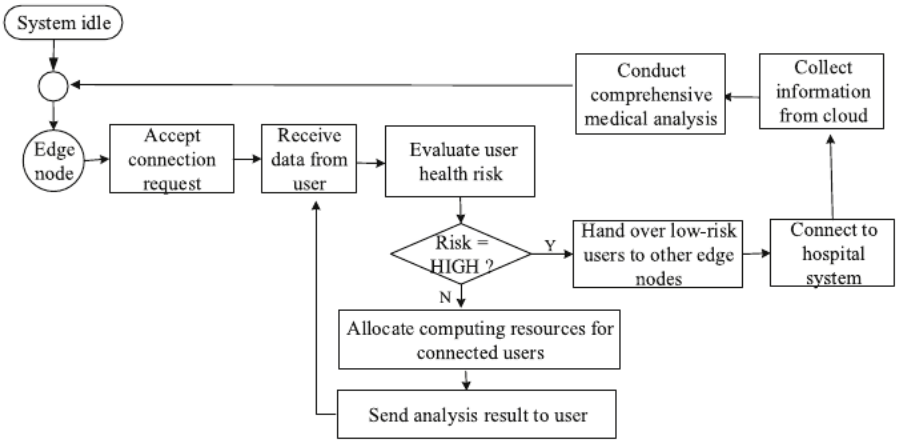


Fig. 3. The flowchart of edge node processing healthcare data.

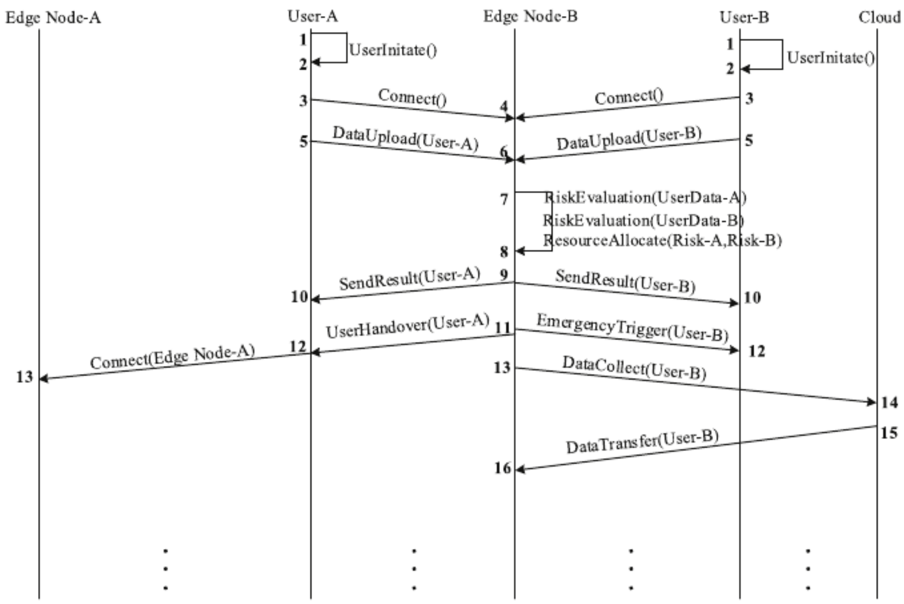


Fig. 4. The sequence chart of healthcare system.

quantify the reasonable optimization degree of the computing resources. We will introduce a QoS quantitative method that can reflect the performance of healthcare system as follows.

(1) User experience quantization

Consider n as the number of edge nodes, and m as the number of the users. We categorize the health risk level of the user into four levels of low, medium, high and danger, and respectively quantify them as 0, 1, 2, and 3. Hence, the health risk level of the ith user is represented by $s(i) \in \{0, 1, 2, 3\}$, and the resource occupancy rate of the ith user is $1/connC(\sigma(i))$, where $\sigma(i) \in [1, n]$ shows the edge node currently connected to the user i, and $connC(j), j \in [1, n]$ shows the number of users currently connected to the edge node j. Therefore, the Overall QoS for all the users can be formulated as:

$$\text{Overall QoS} = \sum_{i=1}^{m} \frac{s(i)}{connC(\sigma(i))} \tag{1}$$

Based on (1), the resource occupancy rate of the user at a high risk level is directly proportional to the QoS. It properly reflects the reasonable optimization degree of the computing resources, so that it can be considered as the method of user experience quantization.

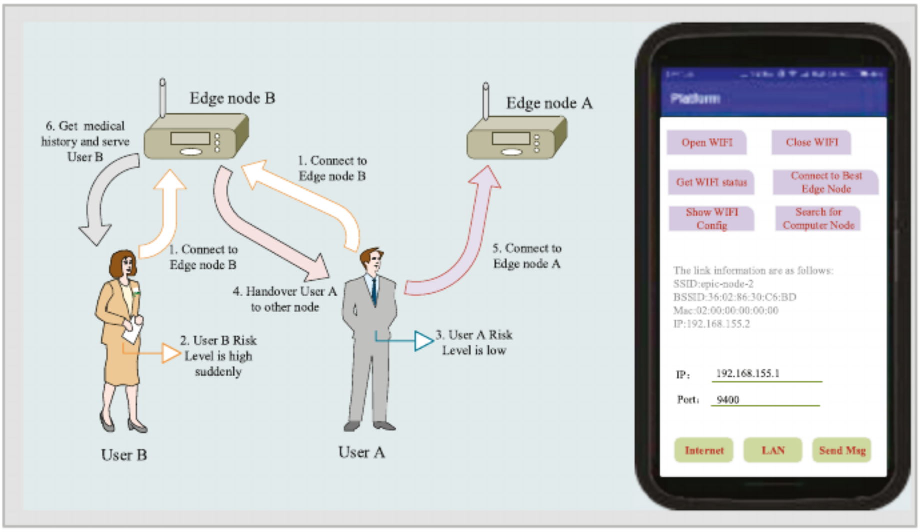


Fig. 5. Implementation of the testbed.

(2) Result analysis

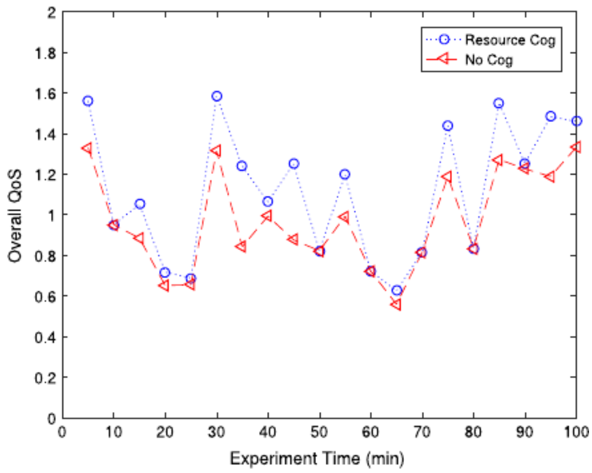
In the experiment, we consider four edge nodes and twelve users, i.e., $n = 4$ and $m = 12$. The computing resource of the edge nodes is the same. We evaluate the user health status every 2 min, observe the network resource distribution 20 times, and then compute the overall QoS, accordingly. Two groups of experiments are performed. The first group does not use the resource cognition, and the user connects to the nearest edge node. The second group uses the resource cognition, and redistributes the resources to the user in the danger state.

Fig. 6(a) plots the experimental results for the overall QoS for two different situations, i.e., with and without the cognitive resource. The result demonstrates that the use of the resource cognition significantly increases the overall QoS, as the system redistributes the edge resources once cognizing a user in the danger state. It then transfers other users in the non-danger state on the edge node connected by the current danger user to other edge nodes, to increase the resource occupancy rate of the current danger user. According to formula (1), the larger the resource occupancy rate of danger user is, the larger the overall QoS will be. Thus, with the resource cognition, the overall QoS has been improved. This indicates that the reasonable resource allocation based on user health status can achieve a better QoS.

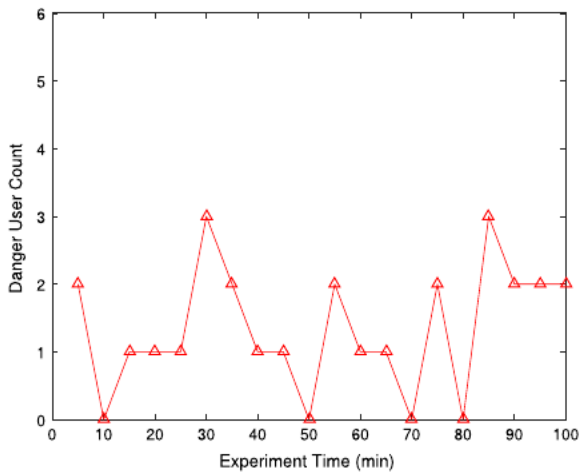
Fig. 6(b) plots the number of danger users with time. In combination with Fig. 6(a), it can be seen that when the number of danger users is zero, there will be no resource redistribution, thus the overall QoS is not changed. When the number of danger users increases, the resource redistribution is conducted, and more resources are distributed to the user with a higher disease level, and accordingly, the overall QoS is significantly improved. In conclusion, the proposed ECC-based healthcare system recognizes the user data, realizes the user-oriented resource distribution, provides a better user experience, and improves the survival rate of the patients.

5. Conclusion

In this paper, we proposed a ECC-based smart healthcare system. This system realized the cognition of data and resource, and solved the problems of inflexible network resource deployment. Specifically, the system first monitored and analyzed the physical health of the smart-clothing users in view of the edge cognitive computing architecture and relevant technologies. Then, based on the data-driven approach, the system implemented a reasonable allocation of edge computing resources. The experimental results showed that the proposed ECC-based healthcare system offered



(a) Overall QoS, with and without the resource cognitive.



(b) Danger user count.

Fig. 6. The experiment results for resource cognitive in ECC-based healthcare system.

a better user QoE in an emergency case, while the computing resources were reasonably optimized. In the future, we will build an emotional recognition system based on ECC. With this emotional detection system, users' emotion will be recognized, and corresponding care will be carried out.

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