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An IoT-Based Framework of Webvr Visualization for Medical Big Data in Connected Health

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ABSTRACT Recently, telemedicine has been widely applied in remote diagnosis, treatment and counseling, where the Internet of Things (IoT) technology plays an important role. In the process of telemedicine, data are collected from remote medical equipment, such as CT machine and MRI machine, and then transmitted and reconstructed locally in three-dimensions. Due to the large amount of data to be transmitted in the reconstructed model and the small storage capacity, data need to be compressed progressively before transmission. On this basis, we proposed a lightweight progressive transmission algorithm based on large data visualization in telemedicine to improve transmission efficiency and achieve lossless transmission of original data. Moreover, a novel four-layer system architecture based on IoT has been introduced, including the sensing layer, analysis layer, network layer and application layer. In this way, the three-dimensional reconstructed data at the local end is compressed and transmitted to the remote end, and then visualized at the remote end to show reconstructed 3D models. Thus, it is conducive to doctors in remote real-time diagnosis and treatment, and then realize the data processing and transmission between doctors, patients and medical equipment.

INDEX TERMS Internet of Thing (IoT), telemedicine, lightweight progressive transmission, medical big data, visualization.

I. INTRODUCTION

Recently, Internet of Things (IoT) has been widely applied in information technology (IT) which is a concept of connecting physical objects via networks for data collection and sharing. The 'Things' in IoT is defined as devices connected to the Internet and able to transmit information to other devices [1]. There are many systems that can be associated with IoT, including green agriculture monitoring system [2], intelligent transportation system [3], environment monitoring system [4], and applications in healthcare industry [5], etc.

The connected health model was proposed as an IoT aspect of healthcare, and the applications of connected health are aiming to improve health care services [6]. Medical IoT is considered as a basis of connected health, where the data exchanging is achieved among doctors, patients and medical equipment [7]. Medical IoT can break the regional restriction to doctors, where medical data and case history can be shared. Meanwhile, the real-time monitoring and diagnosis of patients via Medical IoT greatly reduces the cost and time for transporting patients, and improves the cure rate of

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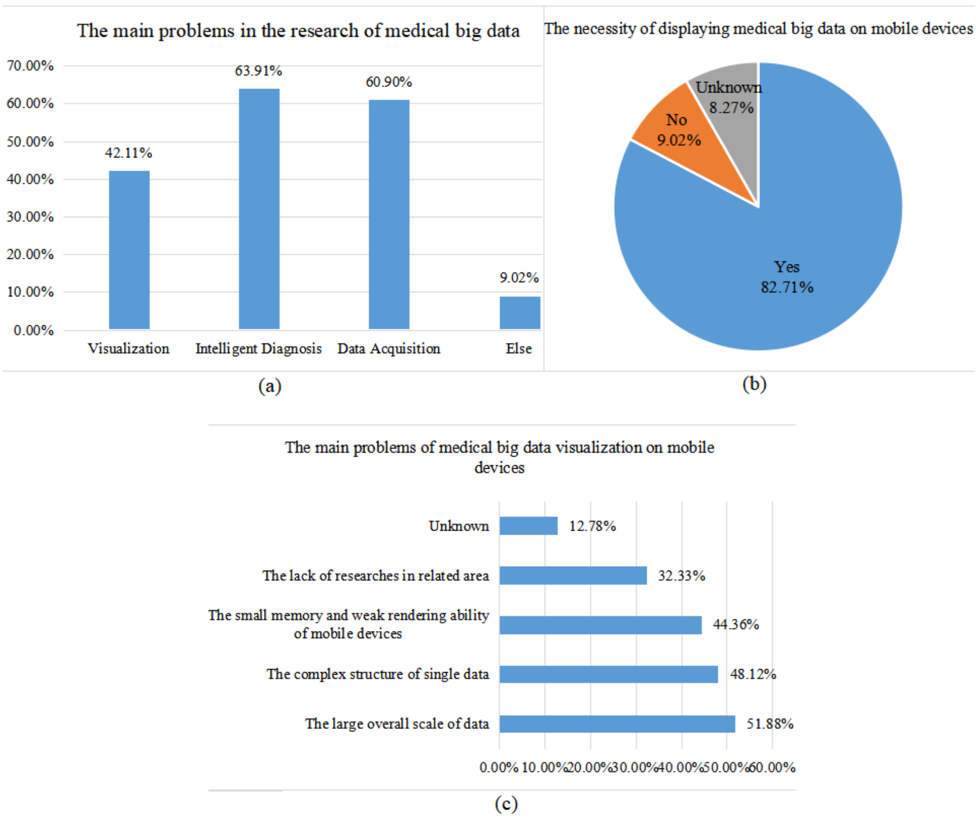

FIGURE 1. The statistical result about medical big data, where (a) represents the result about main problems in the research of medical big data, (b) represents the result about the necessity of displaying medical big data on mobile devices and (c) represents the result about main problems of medical big data visualization on mobile devices.

emergency diseases [8]. The medical big data is defined as a collection based on health-related data which is produced in the entire diagnosis process, from clinic registration to hospital follow-up of patients [9], [10].

In recent years, the visualization of medical big data has taken an important role, where some challenges have occurred. A series of surveys have been taken in medical big data among 133 persons and the statistical result is shown in Fig. 1. We can conclude from Fig. 1(a) that problems in the research of medical big data mainly focus on visualization, intelligent diagnosis and data acquisition. As is shown in Fig. 1(b), most people agree that it is necessary to display the visualization of medical big data on mobile devices. However, there are some main challenges of medical visualization on mobile devices which is shown in Fig. 1(c): 1) The small memory and weak rendering ability of mobile devices; 2) The complex structure of single data; 3) The large overall scale of data.

To solve the problem above, we proposed an IoT-based framework of lightweight progressive coding to visualize medical big data, where both a lightweight progressive transmission method and a four-layered system architecture are proposed. Through our proposed framework, the connection with patients, local doctors and remote doctors is created in the telemedicine system. The lossless medical visualization can be transmitted from local to the mobile remote end, contributing to a more accurate disease diagnosis.

The remaining of the paper is organized as follows. Related works in medical data visualization are introduced in Section II. In Section III, we focus on our proposed four-layered system architecture which is based on IoT. And we describe IoT-based case studies in Section IV to validate the performance of our framework. Finally, we conclude the paper and discuss future work in Section V.

II. REALTED WORK

Medical data is a kind of big data, and medical data visualization can help medical experts analyse data model captured by a series of original images. Recently, medical data visualization has attracted more and more researches, which are described as the following.

The technologies of spark and data visualization were integrated into traditional statistical algorithms by Tang *et al.* to achieve both the reduction of scientific discovery difficulty and the increase of traditional statistical operating speed [11]. Macedo *et al.* proposed a semi-automatic method based on the marker-free augmented reality to achieve the real-time medical data visualization in [12], where a series

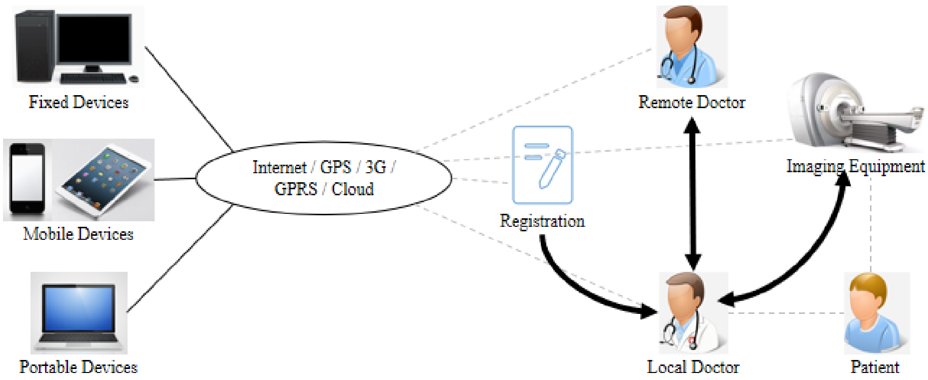

FIGURE 2. The framework of medical big data visualization based on IoT.

of computed tomography (CT) images are used to construct a medical volume data. Then both the KinectFusion method and a variant of the Iterative Closest Point (ICP) method are introduced when forming the visualization model of a patient's head. The experimental results demonstrated that a real-time data visualization can be obtained on the basis of a typical volume size and the occlusion is also supported. Meanwhile, a user collaborative framework with medical data visualization was introduced by Lavrič *et al.* [13], focusing on the user-shareable 3D view-aligned annotations. And a series of experiments show that the views of the end doctors can be described directly and the availability of remote collaboration is greatly improved as well.

Frink *et al.* proposed a new architecture of multidimensional clinical data visualization on the basis of mobile platforms and web, where clinical data is reorganized into a time-based visualization [14]. In different time periods, data can be interpolated over longer frames and finally presented in various colors or shapes for visual result. The experimental results demonstrated that IoT-based clinical data visualization contribute to a real-time and time-saving diagnosis. Besides, a novel graphical tool was designed by Galletta *et al.* to visualize and monitor the health status of patients via a series of IoT-based devices, wearable sensors, etc [15]. A MongoDB is used to store a large amount of collected data and data format of GeoJSON was introduced to perate historical data and real-time physical acquisitions. It can be seen that a good visualization performance has been achieved for most users.

Moreover, the security in the process of medical data visualization should be taken into account. In [16], Mohanty *et al.* introduced a cloud-based framework of data visualization to improve the data security. In the framework, a volume ray-casting pipeline was proposed aiming at hiding secret medical data information. Fan *et al.* also designed a lightweight radio frequency identification (RFID) protocol to enhance medical security, where necessary information are collected by RFID tags for further data processing [17]. On the basis of two-dimensional discrete wavelet transform, Elhoseny *et al.* proposed a hybrid model to protect the security of diagnostic next data [18]. It is demonstrated by experimental tests that patients' data are effectively hidden in the transmitted cover images.

III. SYSTEM DESIGN

A definition of "Internet plus" has been introduced with the arriving of Web 2.0 era, contributing to a new technology of WebVR technology such as internet plus virtual reality technology [19]. In this section, we proposed a framework of lightweight progressive coding for the WebVR visualization of medical big data which is shown in Fig. 2. Patients will be diagnosed by local doctors following registration and medical images will be taken to assist the diagnosis when necessary. The original images will be digitalized, processed, and visualized for local doctors for diagnosis. Meanwhile, the visualization data can also be transmitted to remote doctors' devices including mobile devices, portable devices and fixed devices by lightweight progressive transmission, contributing to the disease diagnosis by remote doctors. The remote doctors will feedback information to local doctors after diagnosis.

A. THE DESCRIPTION OF SYSTEM ARCHITECTURE

Our proposed system architecture based on IoT is expressed in Fig. 3, which presents an end to end process of transmitting medical big data for visualization in connected health.

As shown in Fig. 3, connections of patients, local doctors and remote doctors are established via the architecture. There are four layers contained in the proposed architecture: 1) sensing layer, 2) analysis layer, 3) network layer, and 4) application layer.

The sensing layer is the lowest layer in our IoT-based architecture, which is used for data acquisition. A series of medical imaging equipment are used as sensors to get original images of patients, including Computed Tomography (CT), Optical Coherence Tomography (OCT), Magnetic Resonance Imaging (MRI), Functional Magnetic Resonance Imaging (fMRI), etc. The original images are collected at this layer and then serve as inputs to the upper analysis layer.

The analysis layer is the layer to process original images and achieve the connection between local doctors and

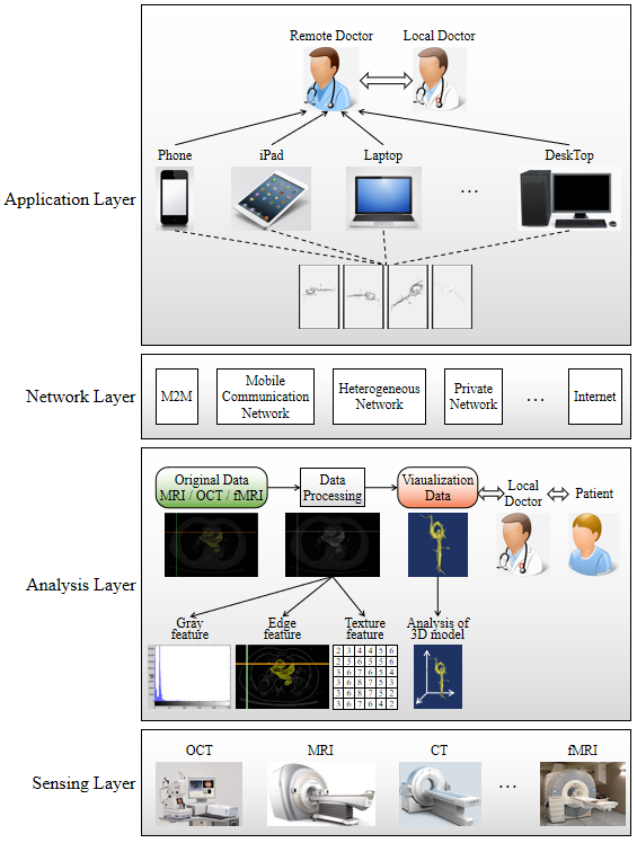

FIGURE 3. The IoT-based system architecture of medical big data visualization in connected health.

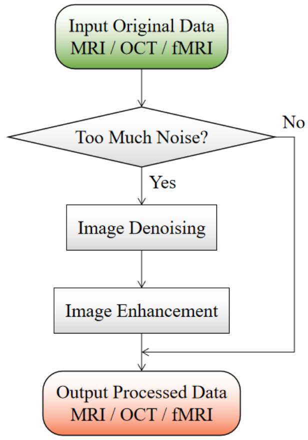

FIGURE 4. The flowchart of data processing in the analysis layer.

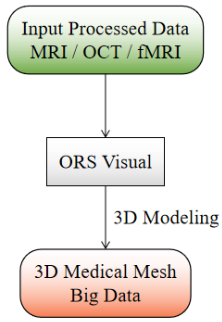

FIGURE 5. The flowchart of data visualization in the analysis layer.

patients. The original data from sensing layer such as CT, MRI, fMRI are visualized after data processing. The obtained visualization data can be inspected by both local doctors and patients. The visualization results can help local doctors to understand patient's condition more concretely to prescribe an effective treatment plan. The visual results also ease the doctor-patient communication by visualizing their conditions. An improved patients' awareness of their conditions can increase the therapeutic effect as well. In this layer, data analysis tools are available to local doctors such as feature extraction, including gray feature, edge feature, texture feature. The attributes of a 3D model can also be analyzed such as length, width and height. Moreover, if local doctors need assistance to get accurate diagnosis or treatment, the visualization data can be shared with remote doctors for further diagnosis via the network layer.

In the network layer, various transmission or reception networks including machine-to-machine (M2M), mobile communication network, heterogeneous network, private network, Internet, etc., are taken into account in the consideration of application requirements. In this layer, we proposed a lightweight progressive transmission for the WebVR visualization of medical big data to reduce the size of data in each transmission process and shorten the transmission time. Through the proposed lightweight progressive transmission based on Internet, the visualization data obtained from the network layer will be transmitted to the application layer.

The application layer focuses on service provision to the remote doctors. The medical big data are received and visualized through mobile devices (e.g. mobile phone, iPad), portable devices (e.g. Laptop), and fixed devices (e.g. Desktop). The remote doctors analyze the visualization results to get corresponding diagnostic results, and also communicate with local doctors via established communication links.

B. DATA VISUALIZATION AND ANALYSIS

In Fig. 3, both data processing and data visualization are necessary in the processing data. The flowchart of data processing is shown in Fig. 4. An original data (e.g. MRI, OCT, fMRI) will be judged whether there is too much noise. And as for original images with too much noise, image denoising is used including median filtering, mean filtering, Gaussian filtering, etc [20]. Moreover, the process of image enhancement mainly based on contrast information is also introduced to reduce image noise [21].

Moreover, as shown in Fig. 5, the data visualization in the analysis layer is achieved by ORS Visual. The regions of interest (ROI) are extracted from input processed images and then visualized into 3D medical mesh big data through ORS visual [22], [23].

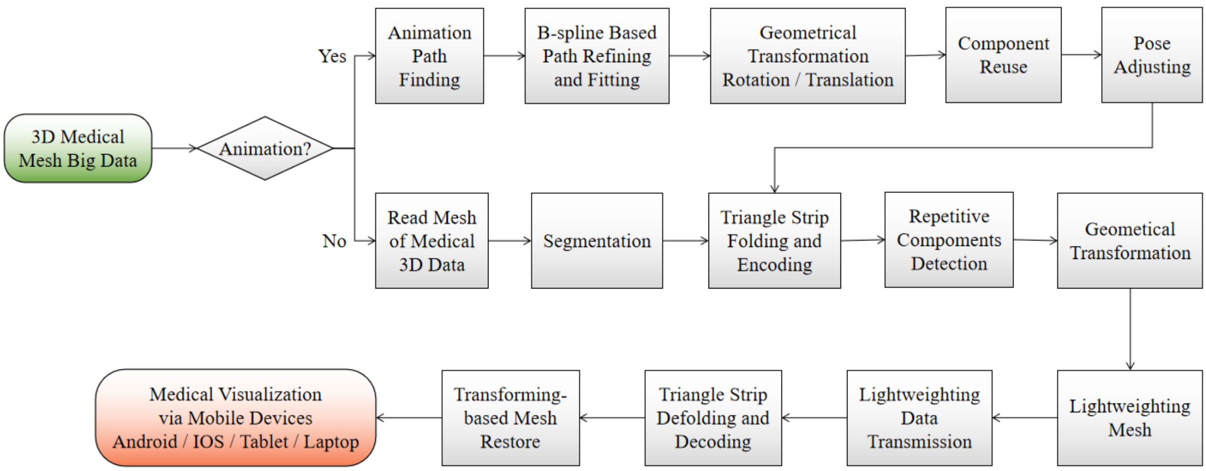

FIGURE 6. The flowchart of lightweight progressive transmission based on Internet in the network layer.

C. DATA TRANSMISSION

The process of lightweight progressive transmission on the basis of Internet is described in Fig. 6. The input 3D medical mesh big data is firstly justified whether it is an animation. If the medical big data is presented as an animation, the animation path will be found and then produce a path refining and fitting on the basis of B-spline. Then the geometrical transformation is used including rotation and translation, etc., where followed by the component reuse and pose adjustment. If the input 3D medical mesh data is not in the form of an animation, the data will be read and then segmented. Next, after the process of pose adjusting of an input animated data or the segmentation of an input non-animated data, a triangle strip folding and encoding is introduced for the repetitive components detection. Moreover, the geometrical transformation is used again for the next lightweight mesh. In this way, the lightweight medical big data is transmitted and the process of triangle strip defolding and decoding is taken into account to have a transforming-based mesh restore [19], [24]. Finally, a medical visualization of medical big data at the remote end is achieved via mobile devices including mobile phones, iPad, and Laptop, etc.

D. SECURITY OF PROPOSED SYSTEM ARCHITECTURE

The point-to-point protocol (PPP) is used in data transmission. A point-to-point connection is established via dial-up or special line, so that data packets are transmitted between the same units, and the format of data frames is shown in Table 1 [25]. In the process of data transmission, disease diagnosis and treatment, it is necessary to protect both privacy and safety of a patient. Disclosure of patient data can threaten the safety of either patients' property or life. For example, information about the blood type and related allergic reactions of a patient can be leaked or tampered without any protective measures, leading to improper treatment in emergencies, and tampering with the surgical treatment scheme of a patient can also lead to exacerbation and even

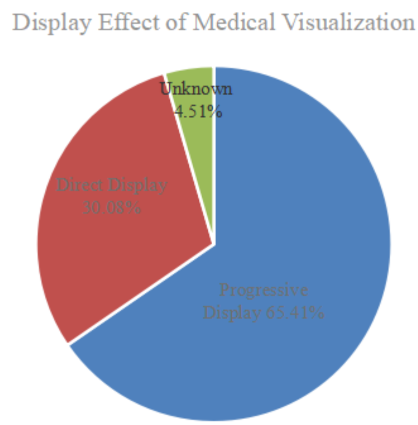

FIGURE 7. The investigation result of the display effect of medical visualization among 133 persons.

life-threatening [26], [27]. In view of the security problems, we stipulate that users should be firstly authorized when logging in the system. And only patients themselves, local doctors and remote doctors concerned with patients have the right to view patient data. Moreover, when local doctors transmit patient data to remote doctors, a serial number of the patient data will be generated, and specific information such as patient's name, ID number, etc. will be hidden. Remote doctors rely on serial numbers of transmission data to distinguish data of different patients or different data of a same patient.

IV. CASE STUDY

In this section, we take a case study as an example of our proposed framework of medical big data visualization on the basis of IoT. Before taking the experiment, we investigated the display effect of medical visualization medical big data on mobile phone among 133 persons. And the investigation results are shown in Fig. 7.

TABLE 1. The format of PPP data frame.

Byte Number	1	1	1	2	Variable	2	1
Field Name	Flag	Address	Control	Protocol	Information Domain	Frame Check Sequence	Flag
Data Sample	0x7E	0xFF	0x03				0x7E

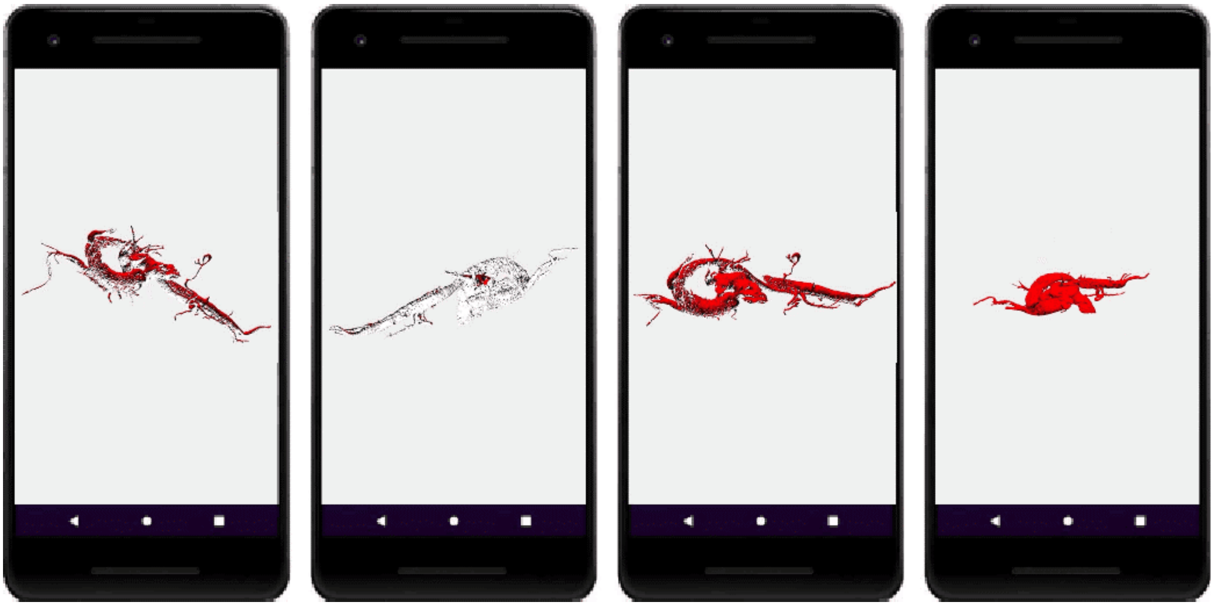

FIGURE 8. The final results of a vascular model shown on a mobile phone representing four different states.

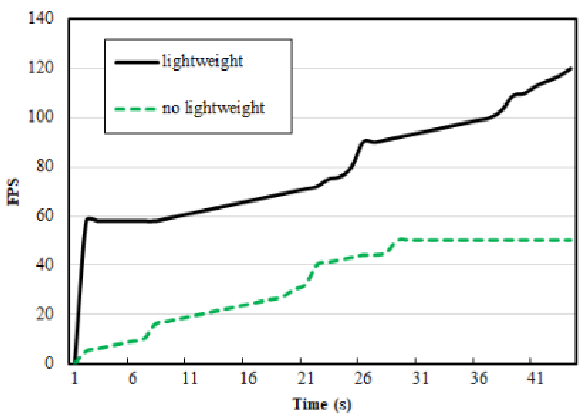

FIGURE 9. A contrasting experiment of visualization in FPS, where the results of lightweighting and no lightweighting are contained.

It can be seen that most people agreed that a progressive display of medical big data has a better visual effect. The progressive display of a vascular model on mobile phones is shown in Fig. 8.

Meanwhile, the result of the frame per second (FPS) in rendering with the increasing time is shown in Fig. 9, where our proposed method with lightweight and traditional method without lightweight are compared. The contrasting experiment demonstrates that with the time increasing, the FPS with lightweight is always higher than that without lightweight and has a sustainable growth, where the FPS of no lightweight remains at 50 FPS after 30 seconds.

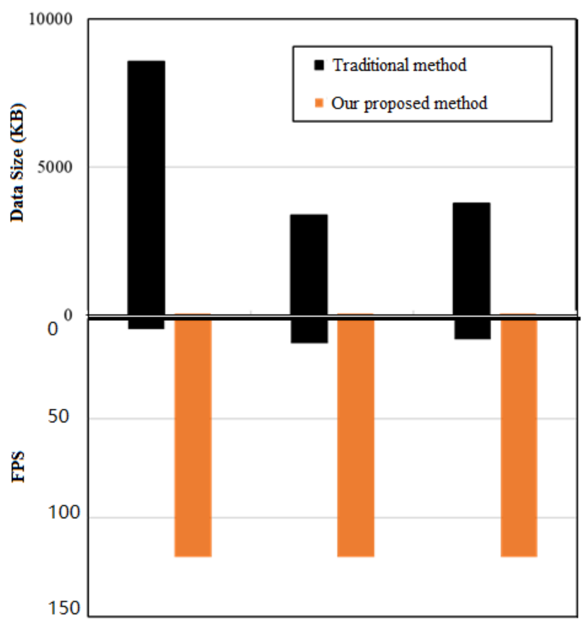

FIGURE 10. A contrasting experiment of visualization in FPS on the basis of three specific data, where the results of lightweighting and no lightweighting are contained.

As it is shown in Fig. 10, three specific data ranging from 0 and 10MB are selected to compare FPS in rendering. Experimental results show that more frames are transmitted per second via the method of lightweight in the case of

FIGURE 11. The system interface of remote doctors on the mobile phone.

FIGURE 12. The system interface of remote doctors on the laptop.

different data sizes, representing that our proposed algorithm has strong ability of both data processing and rendering on the end of mobile Internet. Moreover, the same FPS of different data demonstrates the stability of our proposed method.

Moreover, the system interface of remote doctors on mobile phones and laptop are respectively shown in Fig. 11 and Fig. 12. As shown in Fig. 11, remote doctors can see visualization data from local doctors and send feedback information to local doctors. In Fig. 12, patients' cases and corresponding medical data visualization are contained in the module of files. In the module of diagnosis, remote doctors can have a visualization of transmitted data and then send feedback information to local doctors. Some classical cases and corresponding treatment schemes are included in the module of data. In the module of contact, a local doctor can choose the remote doctor he wants to communicate with.

V. CONCLUSION

In our study, we designed an IoT-based framework consisting of a four-layered system architecture including the sensing layer, analysis layer, network layer and application layer to achieve a telemedicine system. A lightweight progressive coding is proposed within the framework to visualize medical big data. The lightweight progressive transmission guarantees the transmission efficiency and lossless transmission of original medical visualization data. Remote doctors can see visualization data via mobile devices. By establishing a connection between remote doctors and local doctors, we achieved a real-time remote assisted diagnosis of patients. A series of experimental results demonstrated the performance of our proposed solution in terms of data processing and rendering on the end of mobile Internet. In future works, security in medical data visualization and transmission should be taken into account. Multiple encryption algorithms should be used to encrypt the transmitted data, contributing to a protection of patients' privacy.

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