Internet-Based Unobtrusive Tele-Monitoring System for Sleep and Respiration

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ABSTRACT This research is about new advances in the application of remote bio-signal monitoring technology. An unobtrusive IoT bio-signal measurement system is attached to a bed using a very thin strip sensor, then the user's sleep efficiency and respiration rate can be measured with accuracy similar to that of an existing FDA-approved sleep tracker. In particular, in this study, we propose a ubiquitous central monitoring system that links an existing, personal use, unobtrusive measurement system to cloud-based systems via WiFi transmission. The proposed monitoring system simultaneously collects, stores, and displays the data from multiple devices using a web server as well as PC and mobile platforms such as personal smart devices. In this study, we implemented a system for the real-time transmission and display of data from multiple unobtrusive systems and validated that there were no problems associated with sending and receiving data at distances of 300 km with around a one-second delay. In addition, we evaluated the tele-monitoring system's data processing time, CPU usage, and memory usage as the number of users was increased. Each user transmits an average of 810 bytes of data including information such as user id, time stamp, data for each channel, respiration rate and sleep status. We observed that the average data processing time was 0.15 seconds, average CPU usage was 5.01%, average memory usage was 0.1% assuming 10 users connected simultaneously. These results are expected to be useful in guiding future similar personal, public, and clinical applications of this technology.

INDEX TERMS Biomedical monitoring, biomedical telemetry, health information management, Internet of Things, remote monitoring.

I. INTRODUCTION

According to the United Nations, globally, there were 962 million people aged 60 years or over in 2017, this represents an increase of 152 percent over the 383 million older people there were in 1980. This number is projected to grow to 1.4 billion by 2030 and, by 2050, to nearly 2.1 billion [1], doubling its 2017 size. Therefore, it is crucial to develop and implement new strategies and technologies in order to provide better health care services at an affordable price to the aging population while ensuring maximum comfort, independence, and participation among this group.

Remote patient monitoring (RPM) based on Internet-of-Things (IoT) devices is an evolving and growing area of healthcare innovation [2]–[7]. In the past, telemedicine and e-health were common terms used more broadly to capture patient data from remote places. Over the last 10 years, RPM has been rapidly extended to cover the concept of monitoring and treating a wide range of people, including chronic, sick, elderly, and postoperative patients [6], [8]. Recent studies have reported that RPM is effective in treating patients and improving the quality of care [9]–[12]. In addition to studies that demonstrate that IoT technology is effective for remote patient monitoring, remote health monitoring of non-patient users has also been proven effective. Many researchers have studied wireless remote monitoring of heart and blood-related diseases, activity including fall detection and mobility related

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diseases, brain and neurological diseases, body temperature, galvanic skin response, blood oxygen saturation (SpO_2) as well as diabetes [8], [13]. However, many patients are still not interested in sharing RPM data measured in daily life with their physicians due to the poor usability of patient monitoring devices. In addition, physicians do not show confidence in data acquired by RPM [14], [15]. Even if the data collection is performed continuously, it is difficult to make the signal processing analysis reliable and accurate because of the noise generated in daily life such as motion artifacts, detachment of electrode sensors and so on. To solve this issue, unconstrained measurement methods have been developed for long-term reliable monitoring of RPM. The application of this technology varies from sensors attached to the body to ambient sensors attached in the environment as well as a new breakthrough of contactless monitoring that has shown to be effectiveness and only requires the patient to be present within a few meters from the sensor [8], [16]–[18]. In addition, several unconstrained sensing technologies have been proposed such as inertial sensor-based respiration monitoring [19], camera-based gait monitoring [20], fabric-based physiological and behavioral signal sensing systems [21], and a capacitive sensor-based ECG monitoring system [22].

Current unobtrusive monitoring systems are mainly focused on personal purposes such as self-management, but can be used for group monitoring, such as centralized monitoring in an intensive care unit. In order to simultaneously monitor multiple users, a health-IoT framework including sensors, gateway, server, and application should be constructed. With advances in IoT, wireless networking, and distributed system technology, research on multiple user monitoring systems through IoT sensors that gather data from remote places has been able to be carried out. In previous research, we have seen a prototype of a web-based remote patient monitoring system [23]–[26], wireless application protocol (WAP) [23], web based health monitoring system for heart rate, respiration, and body temperature [24], and a web server that collected the data of remote cardiac patients obtained from wearable sensors in real-time [26] been developed.

Recently, many kinds of cloud-based infrastructure for health monitoring systems have been proposed. We have seen examples such as pervasive patient health monitoring system infrastructure based on integrated cloud computing and IoT technologies [27], heterogeneous cloud-based framework consisting of perception, mist, fog, cloud, and application layers for the internet of healthcare things [7], a unified and scalable platform based on IoT gateways, WebRTC architecture, Edge Cloud computing [28], FIWARE cloud platform [29], cloud assisted health monitoring platform that included data analytics, data verification, processing server, storage server through connection gateway between IoT sensors and smart equipment [30], and the privacy preserving online medical service recommendation scheme [31].

Although remote health monitoring technology applying IoT technology is being actively developed in cloud computing environments, several issues still need to be considered. In order to monitor the health status of multiple users in remote places, it is necessary to build a system that supports stable data sensing technology, technology for integrating and analyzing heterogeneous data, and technology for providing important information to health care providers. In addition, wireless network technology that has sufficient security and privacy for processing data extracted from various remote sites and real-time interactive communication between remote data managing server and IoT sensors with a highly scalable structure is needed. Finally, appropriate visualization and information sharing methods are also needed.

Therefore, in this work, we propose a remote patient monitoring system for multiple users using unobtrusive sensors. We have already developed and analyzed a strip type, ultrathin, on-bed, unconstrained bio-signal measurement system for respiratory and sleep efficiency measurements in a previous study [32], in this study we extend those systems to the IoT in order to confirm the possibility of remote monitoring.

The system consists of a cloud computing server that collects heterogeneous IoT sensory signals from multiple sites through wireless communication and visualizes data from multiple users in real-time through a web browser. Evaluations of most previous work were conducted in limited environments using a simulator or public database. However, in this paper, we verify the effect of real physiological signal data on our system by measuring over 8 hours in multiple remote regions in a true to life scenario.

II. MATERIALS AND METHODS

The proposed unconstrained remote monitoring scheme is described in Fig. 1, it consists of an unconstrained on-bed sensor system, gateway, database and server, as well as an application run on a computer or smartphone. The on-bed system measures a subject's physiological and behavioral activity, it then transfers data to the gateway via wireless communication. The gateway collects signals from the multiple sensor systems and transmits the collected data to the server via the cloud. The web-based application enables personal or group monitoring in both stationary devices and mobile devices. In this scheme, users can record and self-monitor their status using a smartphone, and the caregiver can remotely monitor the status of the target via the web and take actions when necessary.

A. UNCONSTRAINED STRIP-TYPE SLEEP MONITORING SENSORS

In previous research, we proposed two kinds of strip-type on-bed force sensing devices [32], these systems were modified for use in this research. The first sleep monitoring sensor measures force based on the piezoelectric characteristics of Polyvinylidene fluoride (PVDF). PVDF film has previously been used for unobtrusive monitoring because it is very thin, flexible, and easy to handle [33]. In other words, a PVDF-based sensor could be developed so it is thin and small enough so the user doesn't realize it is there at all. In this research,
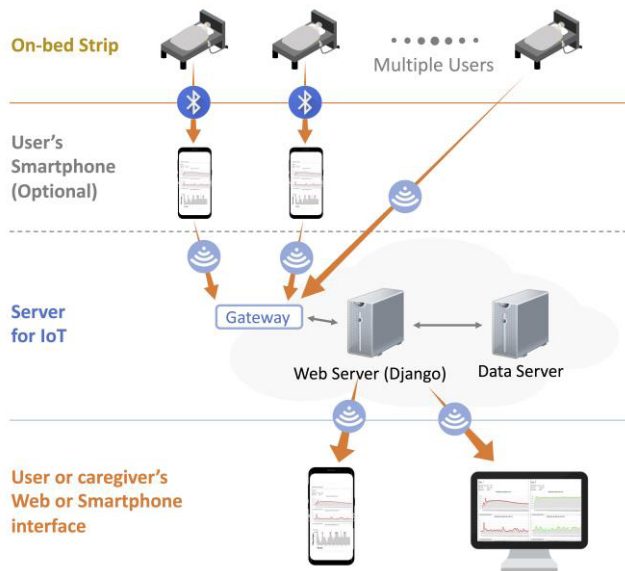
FIGURE 1. The overall scheme of unconstrained remote personal or group monitoring platform.

FIGURE 2. Structure of strip-type unobtrusive sensors. (a) The PVDF-based thin and flexible force sensor, (b) FSR sensor.

TABLE 1. Specification of the developed data acquisition module.

Property	Description	Unit
ADC bit depth	14	bit
Maximum sampling frequency	1	kHz
WiFi Key Features	802.11 b/g/n 802.11n (2.4 GHz), up to 150 Mbps	N/A
Security	AES Hash (SHA-2) RSA ECC Random Number Generator (RNG)	N/A

a PVDF-based force sensor was developed by a screen-printing method. We screen-printed silver paste on PVDF, then covered it with a 0.05 mm thick adhesive polyethylene terephthalate (PET) film and electromagnetic shielding fabric in order to reduce external EM noise. Ultimately, the developed sensor size was 40 mm × 750 mm × 0.25 mm (width × length × thickness) and it had a < 4 ms response time. Two rows of force sensors with a size of 12 mm × 720 mm × 0.13 mm (width × length × thickness) were packed in parallel for multi-channel sensing. Fig. 2 shows the structure and dimension of the developed strip force sensor. The second sleep monitoring sensor measures piezo resistive force using the FSR408 sensor (Interlink Electronics, CA, USA).

The data acquisition module consists of a micro-controller unit (MCU), a Bluetooth module, a microSD card slot, a real-time clock (RTC), and an internal battery. The MSP432P401R (Texas Instruments, Dallas, USA), which supports low-power operation and has a 14-bit analog-to-digital converter (ADC), was used for data conversion and transmission. The sampling frequency was 1 kHz. The measured data was transmitted through WiFi. Table 1 presents the key features of the developed data acquisition module. Fig. 3 shows the analog and digital circuitry of the developed system. In this figure, we can see the analog front-end was designed as an assembly type for expansion. The developed sensor is attached to the mattress using adhesive tape to set it so it crosses the human body, the whole setup is then covered with a mattress cover. The sensor can then be wired to the acquisition system powered by AC or battery. The installation and use of the developed system are presented in Fig. 4.

The sleep efficiency and respiration rate detection algorithm block diagram are shown in Fig. 5. The overall algorithm involves analyzing the awakening and respiration rate.
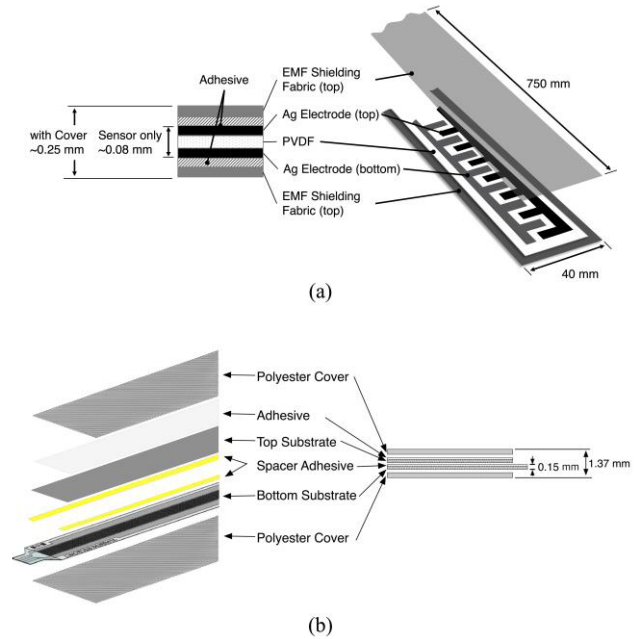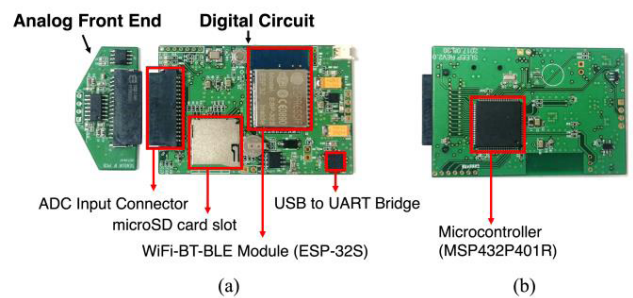

FIGURE 3. Analog and digital circuitry and components of the developed system.

These algorithms are interconnected and are a part of the awakening detection that precedes the respiration rate detection. For awakening detection, it is first determined whether each sample of data being measured is during wake or sleep, it is then determined whether the 30s epoch is during wake or sleep, after which the sleep efficiency is calculated by dividing sleep time with total sleep time. In this case, the 30s epoch is based on the criteria of the general PSG test.
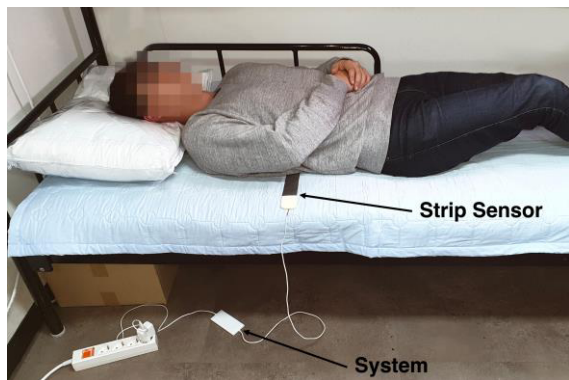
FIGURE 4. Example of the sensor and system's installation and use.
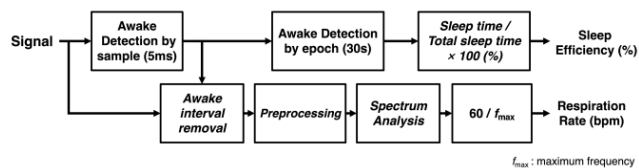

f_{max} : maximum frequency

FIGURE 5. Algorithm block diagram for awakening and respiration rate detection using movement signals.

For respiration rate detection, we used the awakening sample as determined from the awakening detection process. First, we remove the awakening interval from the respiration analysis, then calculate the maximum power from the power spectrum of the measured signal after preprocessing including filtering. In order to calculate the maximum frequency by time, spectrogram analysis is used to calculate the spectrum. In previous research, the developed system was evaluated through a clinical study with 39 sleep disorder subjects and compared with PSG. The developed system showed 79.4% accuracy for sleep efficiency and 76.4% accuracy for <1 bpm error in respiration rate detection, representing accuracy similar to those of other commercialized wearable systems [32].

B. TELE-MONITORING SYSTEM

Remote monitoring and the tele-health system collects individual subjects' data from unobtrusive strip sensors and mobile devices then visualizes the result through a web application. The remote monitoring system topology and network protocol are illustrated in Fig. 6. In the remote monitoring system, the onboard strip sensor periodically wirelessly transmits multi-channel signals based on the TCP protocol, the acquired multi-channel signals are collected and analyzed by the signal receiver server. The data format transmitted consists of the subject identifier, subject name, data for each channel separated by an identifier, measurement time in Unix timestamp format, and the sampling rate of the signal. The data is parsed based on the identifier and stored in the database. The stored data in the database is periodically transmitted to the web server at 0.5-second intervals. The web server sends data every 0.5 seconds, with the data stored in the data queue of the web server being delivered to the web browser based on a request through the HTTPS protocol.
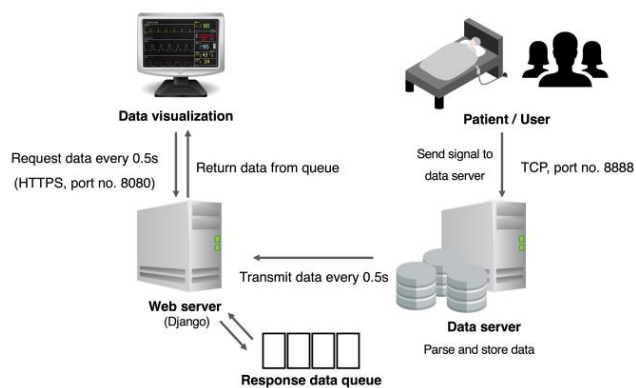

FIGURE 6. Remote monitoring system topology and network protocol.
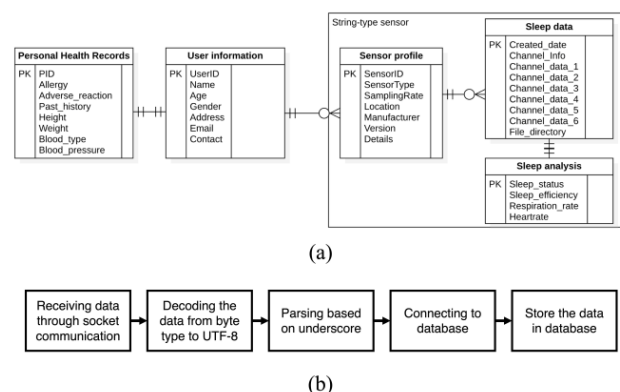

(a)

(b)

FIGURE 7. (a) Database schema and (b) procedure to store and send data for the strip-type sensor.

The response data queue of the web server stores information to be visualized temporarily such as channel information, as well as measurement time based on the current time window. The web server is implemented with the Django web framework.

The database schema in the data server is structured as shown in Fig. 7. The database consists of the user information data, the personal health record data, and string-type sensor data. The user information includes user ID, username, age, gender, contact information such as address, and so on. The string-type sensor data consists of a sensor profile, sleep data, and sleep analysis results. In the sensor profile, sensor ID, type, sampling rate, sensing location, and other details are stored. In the sleep data, the date of data creation, channel information, and each channel's raw or filtered data are stored, this data has a one-to-one relationship with the sleep analysis results. The sleep analysis results include sleep status, analyzed every 30 seconds so as to indicate whether the user is awake or not; sleep efficiency, which indicates how well the user sleeps during the night; respiratory rate, analyzed every 60 seconds. The database associated with string-type sensors is designed to be compatible with other types of sensors in the future. Therefore, any kind of sensor data can be stored and used for sensor profile information, processed

```
(myvenv) mhealth@mhealth-server:~/여행하다/CBP_SLEEP_TEST/tcp/sleep/db$ sqlite3 sleep_data.db
SQLite version 3.11.0 2016-02-15 17:29:24
Enter ".help" for usage hints.
sqlite> select * from SLEEP_DATA
   ...> ;
```

```
40|GACHON|379|16776409|199|16764925|16776899|16764935|1513707299
41|GACHON|379|16776409|199|16764925|16776899|16764935|1513707299
42|GACHON|379|16776409|199|16764925|16776899|16764935|1513707299
43|GACHON|379|16776409|199|16764925|16776899|16764935|1513707299
44|GACHON|379|16776409|199|16764925|16776899|16764935|1513707299
45|GACHON|379|16776409|199|16764925|16776899|16764935|1513707299
46|GACHON|379|16776409|199|16764925|16776899|16764935|1513707299
47|GACHON|379|16776409|199|16764925|16776899|16764935|1513707299
48|GACHON|379|16776409|199|16764925|16776899|16764935|1513707299
49|GACHON|379|16776409|199|16764925|16776899|16764935|1513707299
50|GACHON|379|16776409|199|16764925|16776899|16764935|1513707299
51|GACHON|379|16776409|199|16764925|16776899|16764935|1513707299
52|GACHON|379|16776409|199|16764925|16776899|16764935|1513707299
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55|GACHON|379|16776409|199|16764925|16776899|16764935|1513707299
56|GACHON|379|16776409|199|16764925|16776899|16764935|1513707299
57|GACHON|379|16776409|199|16764925|16776899|16764935|1513707299
58|GACHON|379|16776409|199|16764925|16776899|16764935|1513707299
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FIGURE 8. Web-based remote monitoring system implementation result.

TABLE 2. Performance evaluation of sleep monitoring sensors.

Parameters		Proposed System*		Reference Devices	
Sleep efficiency	PVDF	82.3±13.2	PSG	84.0±10.8
(%)	FSR	82.5±7.2	PSG	78.9±13.1
Respiration rate	PVDF	13.5±2.2	PSG	15.2±3.2
(beats/minute)	FSR	9.2± 1.6	Nasal	9.5 ± 1.7

*performance of sensors was evaluated with different subject group

data information, and analysis information. In addition, since sleep data should generally be collected from sessions of 8 to 10 hours or more, storing all the collected data in a database may be a problem, so the data should be stored in a file format that can support a large amount of data. The personal health record-related database can store a user's health-related information that comes from manual input or real-time sensing data obtained from various kinds of monitoring devices such as wireless weight scale, fitness trackers, and so on. At this stage, it is assumed that the basic data is acquired in the form of string-type data, but the system will be updated to support the electronic medical record protocol conforming to the international protocol in future work. The database data storing process is as shown in Figure 8. Data is received by socket communication, it is decoded in the UTF-8 format from byte type data. Then, the multichannel data is parsed by an underscore identifier and the data server tries to connect to the database. Finally, the parsed and decoded data are stored in the database.

III. EXPERIMENTAL RESULTS

A. SLEEP EFFICIENCY AND RESPIRATION RATE MEASUREMENT

Our previous research confirmed that the developed unobtrusive monitoring system has tenable performance in measuring sleep efficiency and respiratory rate that is comparable with that of a polysomnography (PSG) or wearable sleep trackers (see Table 2). The average sleep efficiency error was 3.6% for the FSR based system and 1.7% for the PDVF based system compared to PSG. In addition, it was confirmed that the FSR system had an error of only 0.3 bpm and the PVDF system
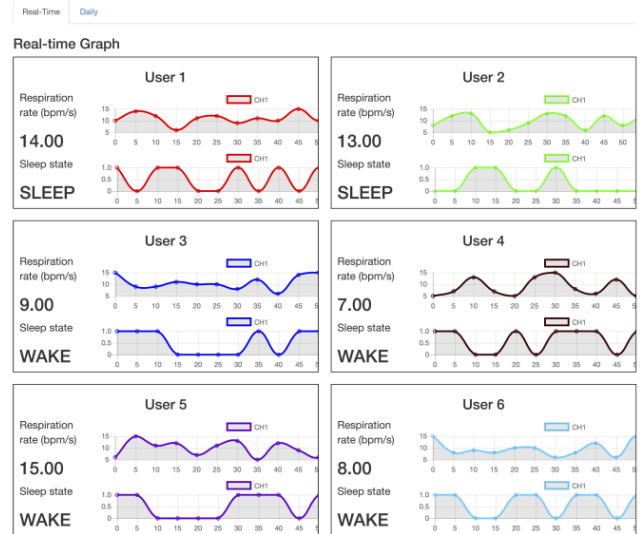

FIGURE 9. Web viewer of web-based remote monitoring system implementation result.

had an error of 1.7 bpm for respiratory rate measurements. All clinical studies are approved by the Institutional Review Board (IRB) of Seoul National University Bundang Hospital (Seongnam, Republic of Korea, IRB no. B-1610/368-301) and Chonnam National University Hospital (Gwangju, Republic of Korea, IRB no. CNUH-2017-274) and written informed consent was obtained from all participants. Comparative devices or indicators such as the PSG and Actiwatch have actually been FDA-approved and are being used in clinical practice. Therefore, it can be considered that the stability of the developed system is sufficient.

B. TELE-MONITORING SYSTEM EVALUATION

We implemented the data collection and web server on Ubuntu 16.04.3 LTS. Data was collected by the TCP network protocol and stored using the sqlite3 database. For web development, the Django web framework was used and the HTTP network protocol was applied. The implementation results from the database and web are shown in Figs 8 and 9, respectively. The specifications of the server used in the experiment are 8 cores with CPU Intel (R) Core (TM) i7-7700 CPU @ 3.60GHz.

In order to evaluate the quantitative performance of the proposed system, we collected multichannel data from one user using the strip-type device in real-time at a remote location over 8 hours. We installed a server and a client at a remote site about 300 kilometers away. Each client (user) transmits an average of 27 bytes of data such as user id, time stamp, data for each channel, respiration rate, heart rate data, and sleep status. For the network evaluation, we observed that the server worked well without error and confirmed that there is no problem in sending and receiving data. For the data processing evaluation, we evaluated the tele-monitoring system's data processing time, CPU usage, and memory usage as the number of users increases. Data processing time

TABLE 3. Performance evaluation of tele-monitoring system.

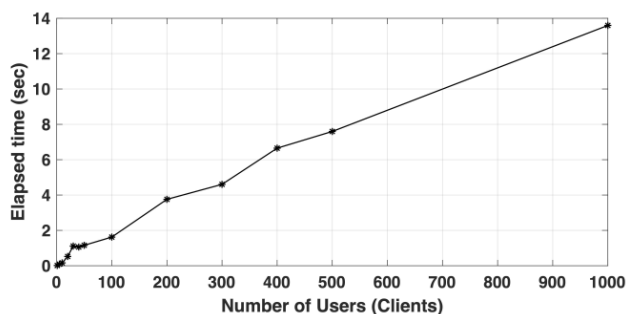| Measurement	Condition (Number of users)						
	1	10	50	100	300	500	1000
Data Processing Time (sec)	0.01	0.15	1.15	1.62	4.60	7.59	13.59
CPU usage (%)	0.62	5.01	29.23	53.52	85.27	86.61	86.14

FIGURE 10. Data processing time by number of users.

was measured from the time data was received to the time the connection was terminated. CPU usage was analyzed by average CPU usage and memory usage was measured every second from the start to the end of processing.

In order to evaluate the performance of the tele-monitoring system as the number of users increases, we used a simulator that creates multiple clients with multiple threads. Assuming the same situation of sending a multi-channel signal from the one user, the data processing time and CPU usage of the system when increasing the number of users from 1 to 1000 was extrapolated and the results are shown in Table 3. The average data processing time was 0.15 seconds assuming the data sent simultaneously over 100 seconds, the average CPU usage per core was 5.01%, average memory usage was 0.1% assuming 10 users connected simultaneously. Fig. 10 and Fig. 11 show the performance of the tele-monitoring system as the number of users increases. Fig. 10 shows the data processing speed of the system according to the number of users sending data at 500 ms intervals. The results of the experiment show processing time increases linearly with increasing numbers of concurrent users. Figure 11 shows the CPU usage as the number of users increases. CPU usage showed logarithmic increases with user numbers, and remained in a specific range in the case of 300 or more concurrent users. Memory usage increased as users increased until 300 users were connected to the system and saturation occurred.

We observed that there was no critical problem in processing speed or CPU usage caused by an increase of users in the current system configuration. However, we found that CPU usage saturated at 86% when we simulated 3000 users. This is because the OS is interrupted by processes for setting OS power options, OS time slicing, or compiler optimizations. We used Python for the client simulator program but due to the lack of optimization while compiling we switched to the C language. In addition, when more than 1,000 users
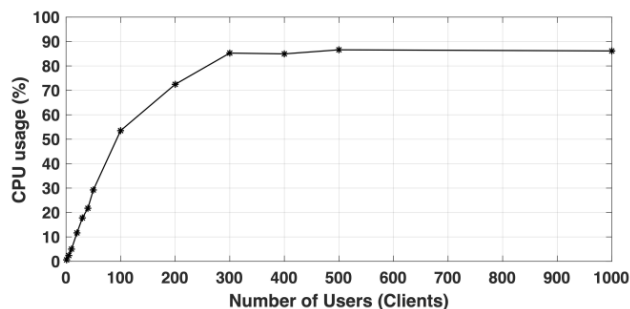

FIGURE 11. CPU usage of system by number of users.

were simulated, connection timeouts and transmission errors began to occur. This is because the current server creates child processes through functions such as *fork* that create requests that go beyond what the current CPU can handle when more than 1,000 users send requests simultaneously. In order to solve this problem, it is necessary to add an exception processing algorithm scheduled by the server for the situation where more than 1000 users are concurrently connected or to solve the problem by adding additional servers. These experiments show it is necessary to design an optimized system using cloud-computing and parallel processing in a distributed computing environment where the large amounts of data generated by over 1,000 users can be handled in the future.

IV. DISCUSSION

The developed system can be used in personal, public, and clinical environments. For personal use, the bio-signal of the individual can be recorded continuously without any movement restriction. This can be used as a daily personal health record and can be used to build personal health big data records through monitoring bio-signals during sleep, this data can be used to detect acute diseases such as systole or respiratory failure. It can also be used for sleep health management, which is the main content covered in this study, and furthermore, it can be used to predict and manage circadian rhythms which are related to daily activities. Currently, most medical practices rely on data obtained after disease outbreaks. However, if the above-mentioned normal bio-signals are accumulated so that causalities of future diseases can be analyzed, it is highly likely to be useful for early diagnosis, which is considered to be important part of future medical care. In addition, in terms of public use, it can be used to monitor health status in public facilities such as day care centers, nursing homes, and public health centers. It can also be used for remote monitoring of situations where it is difficult to provide medical services in person, such as on remote islands or in the mountains. Other examples include application to vulnerable classes such as infants or elderly people living alone, and can support the easy monitoring of daily health care and help health care assistants dealing with chronic illnesses. In addition, through linkage with insurance companies and emergency medical centers, it is possible to

respond to emergencies, monitor daily health conditions, and utilize them in connection with various services. In clinical use, it can be used for regular patient monitoring in general wards, home health care, and remote management.

The developed system is expected to come to be widely used in various fields like those mentioned above, but there are some prerequisites. First, sufficient verification of the developed system is essential. Here, verification refers to a comprehensive concept that includes the evaluation of various environments beyond the testing of several subjects, for example, performance evaluation for various genders, ages, sleeping environments (e.g., mattress type), or usability in various network environments. In particular, in the above-mentioned various situations, stability should be secured in various environments as well as for various subjects, including the elderly and children. Secondly, the communication bandwidth required to acquire a plurality of data at the same time needs to be further specified, as does a strategy for dealing with network errors. Currently, the collected data is one-dimensional bio-signal data in multiple channels. However, the system supports long-term monitoring in consideration of environments where data is collected for at least eight hours based on a stable network environment as well as a flexible data server. We need a data server to manage data volume, variety, and velocity using cluster computing frameworks such as Hadoop or Apache Spark. In addition, it is necessary to apply the cloud computing environment that allows data to be stored and managed over a distributed system rather than building a server in a specific area. Thirdly, privacy and security issues need to be considered. A monitoring system must be provided that protects personal information when storing and visualizing user data. This is required to allow for information to be verified by an accredited institution or individual. In addition, arbitrary and dynamic authorization polices including access time, user roles, level of expertise, and permission level need to be considered so as to provide data access control to the caregiver or experts as necessary. Considering security issues, we need to follow international medical data transfer standards such as DICOM/HL7 as well as public EMR/PHR data formats for integration with various other types of medical data. Finally, currently, single user's usage was verified in a real environment, but multiple user's usage was verified by a simulation. In the future research, it is necessary to evaluate and validate the developed system for the data loss or delay that may occur by the network problem such as communication channel interference in a multiple user environment. As a result, the system developed to be applied to actual situations through commercialization must be verified under various conditions. Nonetheless, the developed system has shown the great possibilities of unobtrusive monitoring.

V. CONCLUSION

In this study, we showed the possibility for remote, ubiquitous monitoring of multiple patients using an unobtrusive system. We implemented a system using real-time medical data

transmission and verified the system performance in terms of CPU usage, data processing time, and memory usage required for transmitting and monitoring 810 bytes of multichannel data for multiple users in an environment where data is transmitted and received from a remote site. The server was equipped with a typical 8-core 3.6G Hz CPU and located 300 km away from the client, we found that we could perform apnea monitoring of up to 300 users over a period of at least 8 hours. We observed that in the cases of monitoring 10 users and 300 users, the system achieved respective data processing times of 0.15 seconds and 4.60 seconds; CPU usage of 5.01% and 85.27; and memory efficiency of 0.1% and 0.1%.

The proposed system, or future systems based on this research, could monitor the physiological status of users without the spatiotemporal limitation using a PC, smartphone or other internet connected personal device. Recently, many IoT healthcare technologies have been proposed, but these have mainly focused on one-on-one or intermittent monitoring. This study is an empirical study on unconstrained IoT healthcare technology, it confirms the possibility of providing remote healthcare in real time through heterogeneous networks for multiple users in actual, real-world situations.

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