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A study of Wearable Sensor Networks with Cloud Access for Health Care

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ABSTRACT

Body sensors, also known as wearable sensors, are increasingly often employed for medical diagnosis and continuous physiological monitoring as ingestible, wearable, and implanted devices. They do, however, generally have a limited budget. Recent technological breakthroughs may give a way to bypass these devices' resource limitations by linking them to smart phones and cloud services. This study offers simulation findings on investigating the viability of 24-hour running time and parallel user support for cloud-enabled apps to evaluate the feasibility of cloud-enabled body sensor networks.

I. INTRODUCTION

Networking sensors around the human body for various healthcare applications has recently attracted attentions of many researchers [1-3]. These sensors often have limited power, storage, and processing resources, hindering them from storing large amounts of long-term sensing data and analyzing complex scenarios that require data from multiple sensors. One possible solution to the problem is to make use of computing resources available to most of the general public, such as smartphones (i.e. mobile health or m-Health [4]) and cloud computing services [5, 6]. Fig. 1 Illustrates a schematic of cloud-connected body sensor networks..

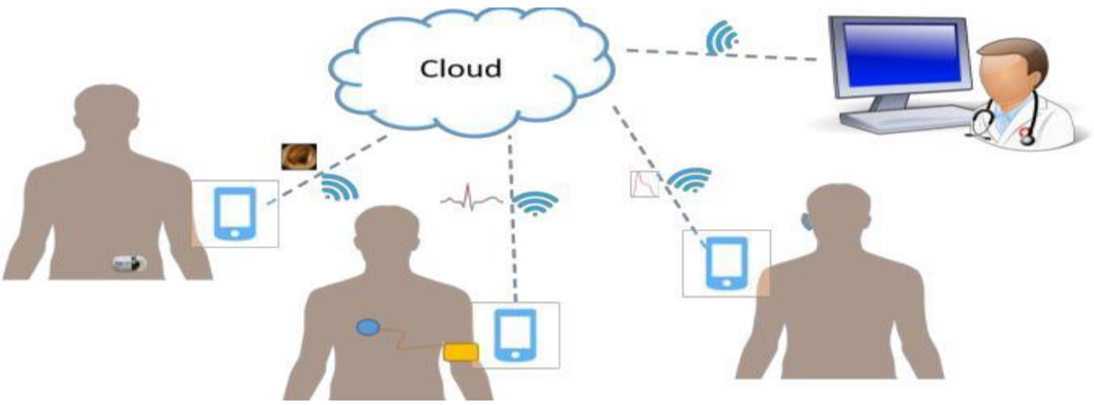

Figure 1. Ingestible and wearable technologies contribute to the formation of cloud-enabled body sensor networks.

This study looks at two scenarios in which cloud-enabled ingestible and wearable devices are used in healthcare. The first scenario depicts how cloud computing resources may be used to improve the diagnostic capabilities of ingestible devices. In the second scenario, a wearable device uses cloud storage resources to provide continuous and long-term physiological monitoring.

II. BODY SENSORS

A. Ingestible Device

A wireless capsule endoscope (WCE) is a typical example
of ingestible body sensors, where the miniaturized device allows the inspection of patients' gastrointestinal (GI) tract unobtrusively [7]. WCE can be equipped with therapeutic features such as the ability to halt GI bleeding through the use of a balloon tamponade effect. [8]. The increasing functionality challenges the design of the WCE. For example, image processing algorithms need to be implemented on the device to recognize bleeding site in real time for the therapeutic function to be initiated instantly. The limited processing power of the device poses strict restrictions to the algorithm design and may hinder the recognition performance of the device. This problem is exacerbated when constructing WCE systems for patients with complex GI problems.

To lessen the storage, analysis, and browsing overhead of the WCE, one recent paper suggested a mobile-cloud aided video summarizing architecture. [9]. Only different frames are transferred to the cloud for further processing, and a lightweight redundant frame removal operation can be performed on the mobile phone. The design was able to reduce the overall computation time on processing and transmission, save energy on the mobile device, and reduce the storage cost [9].

A recent publication from our group tackled a polyp classification problem with a two-step approach based on convolutional neural network (CNN) [10]. The system first recognizes frames in colonoscopy pictures that include polyps, and then categorizes these polyps into histological groups. In comparison to endoscopists' diagnosis on categorising frames into non-polyp, adenoma, and hyperplasia, this work used high-performance computer resources to speed up the algorithm's processing speed, and obtained equivalent precision and a higher recall rate. This CNN-based deep model can be difficult to be deployed on a mobile device with limited computing resources. Nevertheless, with the aid of cloud computing resources, this algorithm may be incorporated with a WCE system for colorectal cancer screening. As conceptually shown in Fig. 2, the mobile device can perform the pre-processing by selecting informative images upon receiving video data captured by the capsule and upload them to the cloud. On the cloud side, the CNN-based polyp
lassification model will be implemented to determine polyp histology types. The cloud services also provide resources for any further improvement of the polyp classification algorithm.

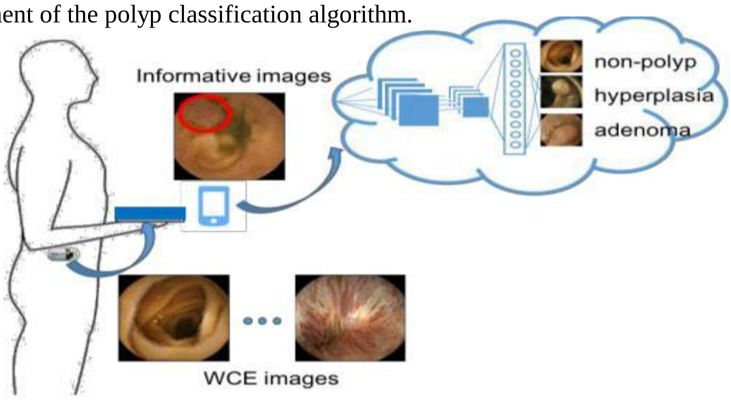

Figure 2. Illustration of a cloud-enabled WCE system for screening and classification of colorectal polyps.

B. Wearable Device

Continuous and long-term physiological monitoring can provide insights into identifying transient physiological events as well as monitoring patients who are critically ill or susceptible to major adverse effects. Multiple body sensors are often needed for a single application [11, 12].

For example, the wearable armband device invented by our group can sample electrocardiogram (ECG) and photoplethysmogram (PPG) by Ag-Ag/Cl electrodes and infrared sensor respectively [12]. The device was further modified to include an accelerometer and gyroscope to collect 6-axis motion signals. The newly integrated motion sensor provides activity information, which can be used for mitigating motion artifacts during data analysis [13]. Data can be stored on device's micro-SD card into 10-minute recording files, approximately 2.65 MB each. To enable the wireless connection of the device, a Bluetooth transceiver module is integrated.

In this paper, we further presented an Android mobile application that manages the Bluetooth connection of the armband and provides an interface between the device and the cloud service, as shown in Fig. 3. Sensor recordings can be transferred to the mobile device continuously for real-time display and storage. Stored data files can be conveyed to the cloud storage service.

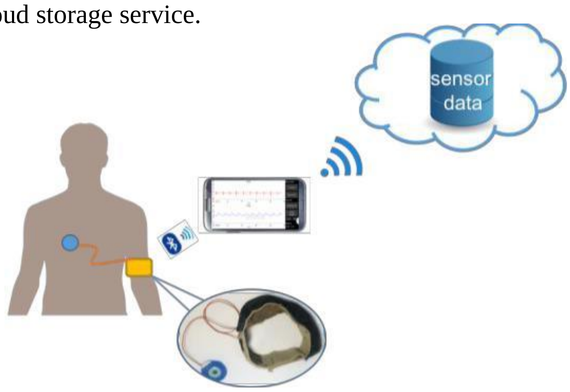

Figure 3. A cloud-enabled wearable device for continually monitoring several physiological signals is depicted.

Two types of cloud services were considered: a commercial cloud storage service and a locally-hosted cloud storage service. The offered mobile software development kit was used to accomplish the direct sending of armband recorded data files to a commercially accessible cloud storage service, Amazon Simple Storage Service (Amazon S3) [14]. (SDK). One advantage of using commercially available cloud storage service is that concurrent user uploading can be handled by the cloud service, and thus reduces development workload.

A cloud service was also simulated on a local workstation with main functions shown in Fig. 4. The Connection Management Unit uses a multi-thread scheme to handle users' requests via socket connections. User Identity Database Unit utilizes a lightweight relational database [15] to store users' identity information for registration and verification. It also keeps a file address for each user pointing to a corresponding location in the File Storage Unit. Fig. 5 shows the protocol for establishing a successful connection. The mobile device starts the connection by sending a connection request with user's identity information. The cloud service verifies the user's identification and reacts appropriately. Unverified connections will be terminated, but users who have verified their identities will be permitted to start the data uploading process, which will be followed by an endmarker to signal completion. A successful uploading session terminates upon the mobile device receives a recipient confirmation from the cloud service.

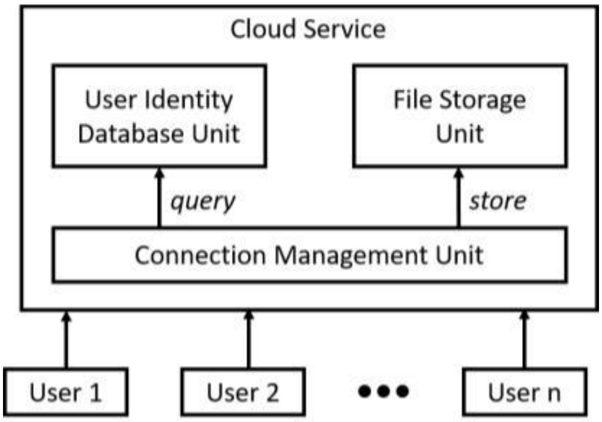

Figure 4. An overview of the design of locally hosted cloud services.

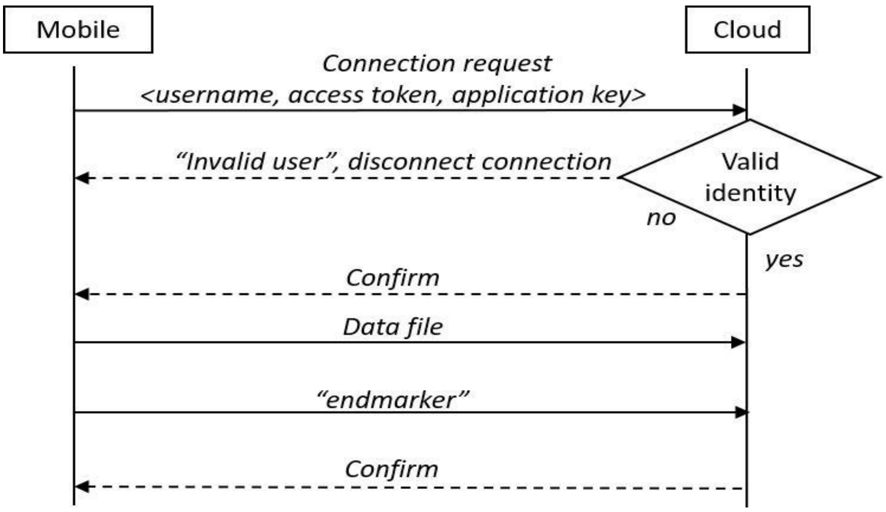

Figure 5. Interactions between the mobile device and the cloud service for data upload.

III. EXPERIMENTS AND RESULTS

A. Experiments

Experiments were conducted to simulate the following scenarios: 1) a single system supporting a 24-hour recording session (single-user), and 2) 50 users concurrently accessing the cloud service (multi-user). The implementation of transferring WCE picture files and wearable sensor data files from the mobile device to the cloud services would be similar since the data was transferred in files. Experiments were conducted on armband sensor data, and similar observations can be made when uploading endoscopic images.

1) Single-user Test

To test the connectivity between a mobile device and Amazon S3, pre-recorded 24-hour armband monitoring data was kept on a Samsung Note 2 Smartphone. A mobile application was set to automatically upload one data file containing 10-minute continuous sensing data every 10 minutes over a 24-hour period, simulating the data transmission for one user during one day.

2) Multi-user Tests

When considering the concurrent user access scenario which can happen during the population-based screening, multi-thread Python applications on a laptop were developed to emulate multiple users' concurrent uploading requests for pre-recorded 10-minute sensor recording files.

Two different tests were performed: 1) 50 concurrent users uploading files to the Amazon S3 periodically over a 24-hour period; 2) different number of concurrent users (1, 10, 20, 30, 40, 50) uploading files to the locally hosted cloud service within the same local area network (LAN) for 10 independent sessions. Each file upload from all participating users was considered as an uploading session. The cloud service was hosted on a Windows workstation (3.30-GHz Intel Xeon CPU with 16 GB RAM).

B. Results

1) Single-user Test

Each uploading job took less than 50 milliseconds, and the average time this user took to upload a file to Amazon S3 for the test was 31 milliseconds. The variable network conditions might cause variations in uploading times. During the test, there was no transmission loss.

2) Multi-user Tests

A Python script was used to imitate 50 people uploading data to Amazon S3 at the same time throughout the course of a 24-hour period. Due to the formation of an initial connection, the first uploading job for all users took longer (16.373 0.641 s) than the succeeding uploading tasks. The average uploading time for each user was determined and presented in Fig. 7 for the succeeding sessions when there were 50 concurrent uploads. Variations in uploading time across each transmission session may be due to the varying network condition over the testing period. The initiations of uploading tasks from different users were not perfectly aligned for each session, which caused further variations. No transmission loss was noticed during the test. It can be noticed that the average time taken for one user to upload a file when there are 50 concurrent users was much longer than the result shown in Fig. 6 for the single-user test. The difference can be caused by several reasons. First, the devices used in these two tests were different. An Android device was used for a single-user test, while multi-users were simulated from a laptop. The different connections to the Amazon S3 may cause the difference on uploading time. Second, the instantaneity of the wireless network introduced more uncontrolled variables into these two experiments. Thirdly, in the multi-user experiment, 50 users shared the same bandwidth, causing a reduced effective bandwidth for each user. The concurrent requests to the cloud service may introduce extra computation at the remote side, which may also contribute to the difference, although the effect of this factor is likely to be small considering the abundant resources cloud computing can offer.

The mean and standard deviation were calculated during ten separate upload sessions with varying numbers of concurrent users. With the increasing number of concurrent users, the uploading time was increased. This was due to the increased computation at the server side to handle the increased number of requests. The increasing number of users also increased the network traffic, which might be another reason for the prolonged uploading time. When considering the 50 concurrent-user case for both Amazon S3 and locally hosted cloud service, commercial storage service achieved over 5 times faster data uploading speed than the locally hosted service.

For the locally hosted service, transmission protocol between the mobile device and the local cloud service prolonged the data uploading time, and all increased data traffic was confined in the same LAN which might further slowdown the transmission process. The superior resources available for Amazon S3 were another big contributor to the uploading time difference. The results showed that the self-designed service has the ability to support 50 concurrent users uploading tasks based on the current setting.

Table I. Data Uploading time with Different Number of Concurrent users Across 10 Independent Sessions

Number of Concurrent Users	Mean Uploading Time by Each User (Mean ± Standard Deviation in seconds)
1	0.382 ± 0.040
10	2.393 ± 0.306
20	4.694 ± 0.722
30	6.877 ± 0.944
40	10.253 ± 2.242
50	14.290 ± 3.737

IV. CONCLUSION

This paper focuses on introducing two examples for cloud-enabled body sensor network applications in supporting advanced ingestible sensor functions and continuous and long-term physiological monitoring. By transferring continuously sampled physiological signals in a 10-minute file format, the cloud-enabled wearable system has the potential to support long-term monitoring. In future, motion artifacts removal function, enabled by motion signals, can be incorporated to further prolong the lifetime of the wearable devices. Another future direction is to utilize the cloud computing resources for data management collected from heterogeneous sources. Point-of-care (POC) devices that do coagulation tests, for example, have been utilised to assist physicians with patient management. Surgical patients have benefited from POC testing and transfusion algorithms, which have reduced transfusion needs and blood loss [16]. Advanced algorithms for integrating POC testing findings with other data types to aid in clinical decision making can be supported with the ample computational capabilities.

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