# Cloud Enabled Wearable Sensor Networks for Health Care

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## ABSTRACT

*Body sensors or wearable sensors are now normally used as ingestible, wearable and implantable devices for medical diagnosis and uninterrupted physiological monitoring. However, they usually have limited resources. Recent advancements in technologies provide a possible solution to overcome the resource limitation of these devices by connecting them with smart mobiles and cloud services. To estimate the feasibility of the cloud-enabled body sensor networks, this paper presents simulation results on testing the feasibility of 24-hour operating time and parallel user support for the cloud-enabled applications.*

## 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 shows a conceptual diagram of cloud-enabled body sensor networks.

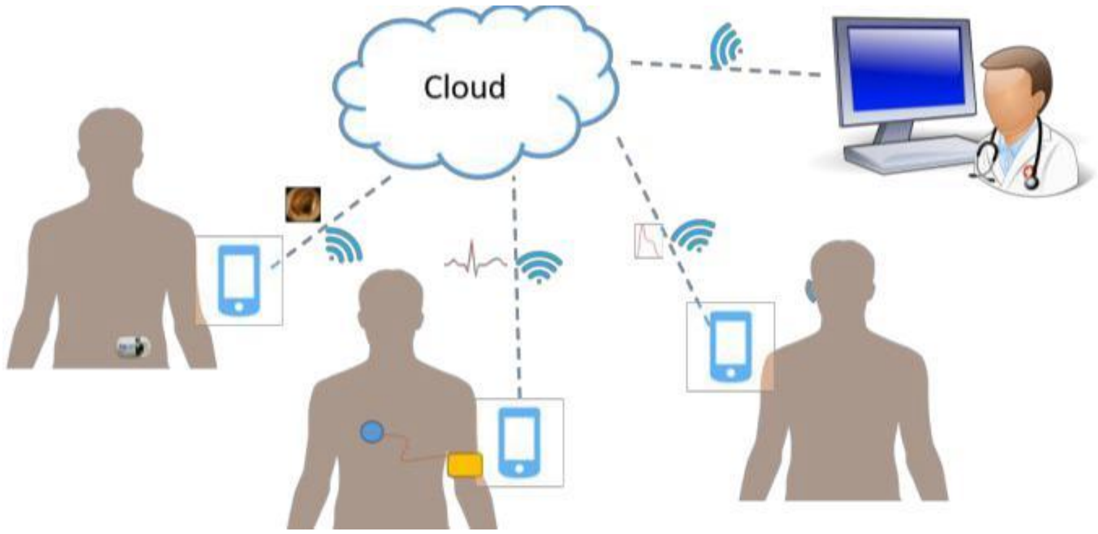


**Figure 1. Examples of cloud-enabled body sensor networks formed in part by ingestible and wearable systems.**

This paper focuses on two examples where cloud-enabled ingestible and wearable devices are applied to healthcare applications. The first example describes a scenario where cloud computing resources can enhance ingestible devices' diagnostic function. In the second example, a wearable device enables continuous and long-term physiological monitoring by utilizing cloud storage resources.

## 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 functions such as stopping GI bleeding by 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 issue is more severe when designing WCE system targeting for complicated GI disorders.

One recent publication proposed a mobile-cloud assisted video summarization framework for WCE to reduce the storage, analysis and browsing burden of the WCE [9]. A lightweight redundant frame removal process can be carried out on the mobile phone, and only dissimilar frames are transmitted to the cloud for further processing. 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 algorithm first detects frames containing polyps from colonoscopy images and then classifies these polyps into histology types. This paper utilized high-performance computing resources to accelerate the processing speed of the algorithm, and achieved similar precision and higher recall rate compared to endoscopists' diagnosis on classifying frames into non-polyp, adenoma and hyperplasia. 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.

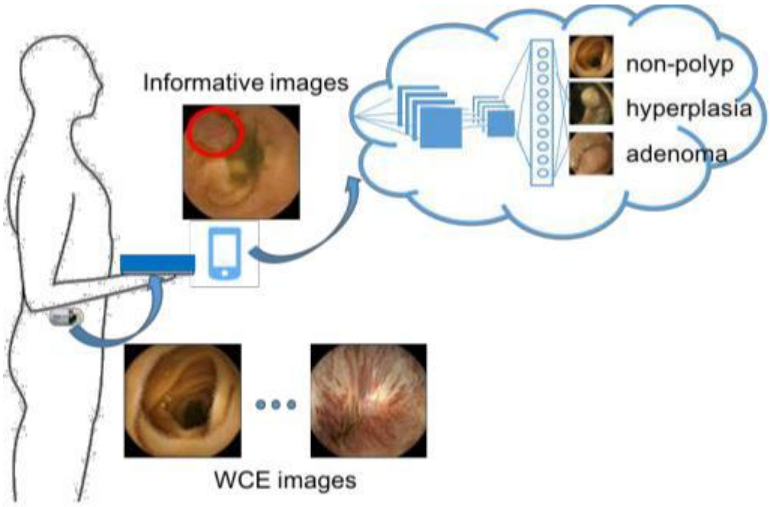


**Figure 2. Illustration of a cloud-enabled WCE system for screening and classification of colorectal polyps.**

## 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.

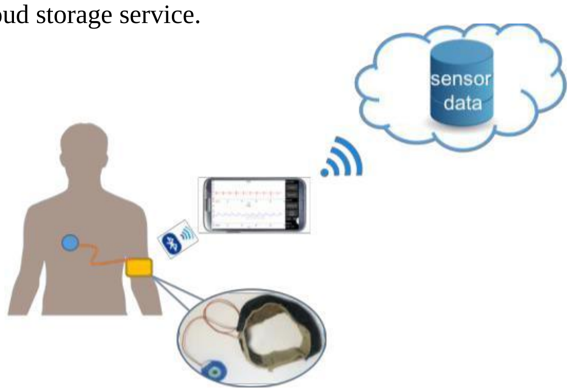


**Figure 3. Illustration of a cloud-enabled wearable system for monitoring multiple physiological signals continuously.**

Two types of cloud services were considered: a commercial cloud storage service and a locally-hosted cloud storage service. The implementation of directly forwarding armband recorded data files to a commercially available cloud storage service, Amazon Simple Storage Service (Amazon S3) [14], was achieved with the provided mobile software development kit (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 user's identity and replies accordingly. Connections from unverified users will be aborted, while identity verified users can then start the data uploading process followed by an endmarker to inform the completion. A successful uploading session terminates upon the mobile device receives a recipient confirmation from the cloud service.

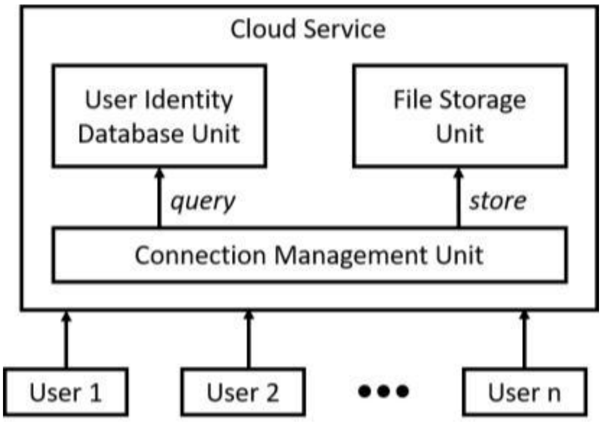


**Figure 4.An overview of locally-hosted cloud service design.**

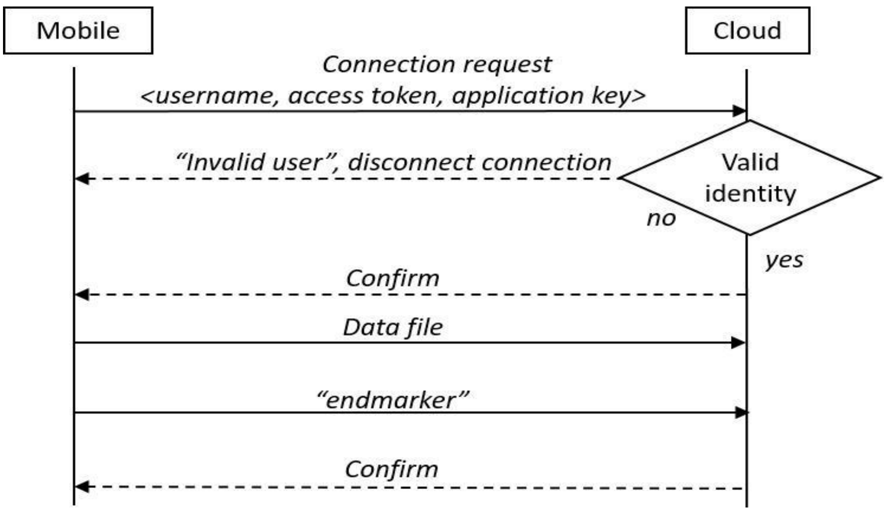


**Figure 5. Interactions between the mobile device and the cloud service for data upload.**

## 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). Since the data were transmitted in files, the implementation of transmitting WCE image files and wearable sensor data files from the mobile device to the cloud services will be similar. Experiments were conducted on armband sensor data, and similar observations can be made when uploading endoscopic images.

#### 1) Single-user Test

Pre-recorded 24-hour armband monitoring data were stored on a Samsung Note 2 Smartphone to test the connection between a mobile device and Amazon S3. 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

Fig. 6 shows the time for uploading a 10-minute sensing data file from the mobile phone to Amazon S3 by one user over a 24-hour period. The user uploaded 144 sensor data files in one day. Amongst them, the recorded result of one data file has been corrupted and was not included in the analysis.


Figure 6. The uploading time of a 10-minute sensing data file from a mobile device to Amazon S3 over a 24-hour period by a single user.

Each uploading task was completed within 50 ms, and the average time for this user to upload a file to Amazon S3 during the test duration was 31 ms. Variations in the uploading time can be caused by the varying network conditions. No transmission loss was experienced during the test.

**2) Multi-user Tests**

A Python application was used to simulate the scenario that 50 users concurrently uploaded data to the Amazon S3 in a 24-hour period. The first uploading task for all users required a longer time (16.373 ± 0.641 s) than the subsequent uploading tasks due to establishment of an initial connection. For the subsequent sessions, the average uploading time for each user when there were 50 concurrent uploads at each session were calculated and plotted in Fig. 7. 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.

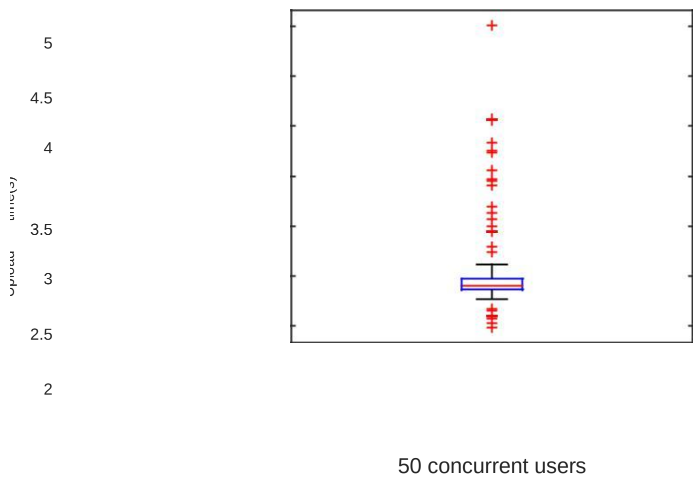


Figure 7. The average time for one user to upload files from the local network to Amazon S3 after initial connection establishment under multi-user test. The average time was calculated by averaging the recorded uploading time over 50 users in each uploading session.

Test results for data file uploaded to the locally hosted cloud services are shown in Table I. The uploading time was considered as the time elapsed between the connection request made by the user and the confirmation message received by the user. Uploading time shown was calculated by averaging the recorded uploading time of all participating users during the test. Mean and standard deviation were presented across 10 independent upload sessions under different number of concurrent users scenarios. 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. For example, point-of-care (POC) devices performing coagulation tests have been used to aid clinicians in patient management. Surgical patients have experienced benefits, such as reduced transfusion requirements and blood loss, owing to the POC testing and transfusion algorithms [16]. With the abundant computing resources, advanced algorithms can be supported to integrate POC testing results with other data types to assist in clinical decision making.

## REFERENCES

[1] C. C. Y. Poon, Y. L. Zheng, N. Q. Luo, X. R. Ding, and Y. T. Zhang, "Wearing Sensors Inside and Outside of the Human Body for the Early Detection of Diseases," in Wearable Sensors, E. Sazonov and M. Neuman, Eds.: Elsevier, 2014.

[2] Y. L. Zheng, X. R. Ding, C. C. Y. Poon, B. P. L. Lo, H. Y. Zhang, X.

L. Zhou, G. Z. Yang, N. Zhao, and Y. T. Zhang, "Unobtrusive Sensing and Wearable Devices for Health Informatics," IEEE Transactions on Biomedical Engineering, vol. 61, pp. 1538-1554, May 2014.

[3] J. Andreu-Perez, C. C. Y. Poon, R. D. Merrifield, S. T. C. Wong, and

G. Z. Yang, "Big Data for Health," IEEE Journal of Biomedical and Health Informatics, vol. 19, pp. 1193-1208, Jul 2015.

[4] S. R. Steinhubl, E. D. Muse, and E. J. Topol, "The emerging field of mobile health," Science Translational Medicine, vol. 7, pp. 1-6, Apr 2015.

[5] R. Buyya, C. S. Yeo, S. Venugopal, J. Broberg, and I. Brandic, "Cloud computing and emerging IT platforms: Vision, hype, and reality for delivering computing as the 5th utility," Future Generation Computer Systems - the International Journal of Grid Computing and Escience, vol. 25, pp. 599-616, Jun 2009.

[6] A. M. H. Kuo, "Opportunities and Challenges of Cloud Computing to Improve Health Care Services," Journal of Medical Internet Research, vol. 13, pp. 1-15, Sep 2011.

[7] G. Iddan, G. Meron, A. Glukhovsky, and P. Swain, "Wireless capsule endoscopy," Nature, vol. 405, pp. 417-418, May 2000.

[8] B. H. K. Leung, C. C. Y. Poon, R. Zhang, Y. L. Zheng, C. K. W. Chan,

P. W. Y. Chiu, J. Y. W. Lau, and J. J. Y. Sung, "A Therapeutic Wireless Capsule for Treatment of Gastrointestinal Haemorrhage by Balloon Tamponade Effect," IEEE Transactions on Biomedical Engineering, pp. 1-1, Jul 2016.

[9] I. Mehmood, M. Sajjad, and S. W. Baik, "Mobile-Cloud Assisted Video Summarization Framework for Efficient Management of Remote Sensing Data Generated by Wireless Capsule Sensors," Sensors, vol. 14, pp. 17112-17145, Sep 2014.

[10] R. Zhang, Y. Zheng, T. W. C. Mak, R. Yu, S. H. Wong, J. Y. W. Lau, and C. C. Y. Poon, "Automatic Detection and Classification of Colorectal Polyps by Transferring Low-Level CNN Features From Nonmedical Domain," IEEE Journal of Biomedical and Health Informatics, vol. 21, pp. 41-47, Jan 2017.

[11] Y. L. Zheng, T. C. H. Wong, B. H. K. Leung, and C. C. Y. Poon, "Unobtrusive and Multimodal Wearable Sensing to Quantify Anxiety," IEEE Sensors Journal, vol. 16, pp. 3689-3696, May 2016.

[12] Y. L. Zheng, C. C. Y. Poon, B. P. Yan, and J. Y. W. Lau, "Pulse Arrival Time Based Cuff-Less and 24-H Wearable Blood Pressure Monitoring and its Diagnostic Value in Hypertension," Journal of Medical Systems, vol. 40, Sep 2016.

[13] Y. Zheng and C. C. Y. Poon, "Wearable devices and their applications in surgical robot control and p-medicine," in 2016 IEEE 20th International Conference on Computer Supported Cooperative Work in Design (CSCWD), Nanchang, 2016, pp. 659-663.

[14] Amazon S3. (2017). Available: https://aws.amazon.com/s3

[15] SQLAlchemy. (2017). Available: http://www.sqlalchemy.org/

[16] L. Enriquez and L. Shore-Lesserson, "Point-of-care coagulation testing and transfusion algorithms," British Journal of Anaesthesia, vol. 103, pp. i14-i22, Dec 2009.