Federated Internet of Things and Cloud Computing Pervasive Patient Health Monitoring System

Jemal H. Abawajy and Mohammad Mehedi Hassan

The authors present a pervasive patient health monitoring (PPHM) system infrastructure. PPHM is based on integrated cloud computing and Internet of Things technologies. In order to demonstrate the suitability of the proposed PPHM infrastructure, a case study for real-time monitoring of a patient suffering from congestive heart failure using ECG is presented.

ABSTRACT

The exponentially growing healthcare costs coupled with the increasing interest of patients in receiving care in the comfort of their own homes have prompted a serious need to revolutionize healthcare systems. This has prompted active research in the development of solutions that enable healthcare providers to remotely monitor and evaluate the health of patients in the comfort of their residences. However, existing works lack flexibility, scalability, and energy efficiency. This article presents a pervasive patient health monitoring (PPHM) system infrastructure. PPHM is based on integrated cloud computing and Internet of Things technologies. In order to demonstrate the suitability of the proposed PPHM infrastructure, a case study for real-time monitoring of a patient suffering from congestive heart failure using ECG is presented. Experimental evaluation of the proposed PPHM infrastructure shows that PPHM is a flexible, scalable, and energy-efficient remote patient health monitoring system.

INTRODUCTION

Healthcare costs in many countries are increasing at an unsustainable rate. In the United States, for instance, healthcare spending is expected to be $4.8 trillion in 2021, which is close to 20 percent of gross domestic product [1]. Factors accounting for the increasing healthcare spending include chronic diseases, waste, and inefficiencies such as over-treatment, and redundant, inappropriate, or unnecessary tests and procedures. In addition, advances in medicine over the last decades have significantly increased the average life expectancy while simultaneously decreasing the rate of mortality substantially. As a result, the number of elderly people has been rising constantly, which is placing a strain on the healthcare services. The need to bring healthcare costs into a sustainable range is an urgent issue that needs to be addressed [2].

One possible way to address the challenges facing the healthcare industry is by caring for patients in their environments such as their residences. A lot of patient categories such as those with chronic disease who need only therapeutic supervision, elderly patients, and patients with congenital heart defects do not need to use a hospital bed as they can be cared for in their homes [2–4]. The challenge, however, is how healthcare professionals can accurately, reliably, and securely monitor the health status of their patients without physically visiting them at their residences. The system must be able to facilitate patient mobility, while at the same time improve their safety and increase their autonomy.

This study addresses this challenge by augmenting existing healthcare systems with inexpensive but flexible and scalable pervasive technologies that enable long-term remote patient health status monitoring. Recent advances in the Internet of Things (IoT) [12] and cloud computing (CC) [13] have made it practically possible to transform the healthcare sector. As the healthcare system increasingly values efficiency and outcomes, the adoption and diffusion of IoT and cloud can play a significant role in arresting the spiraling healthcare costs without impacting the quality of care provided to patients [4]. Although the integration of IoT and CC would be a great innovation in contemporary medical applications [7], remote patient health status monitoring systems that integrate IoT and CC have received less attention [4]. Therefore, despite all of the possibilities that IoT and CC technologies offer, there are some significant obstacles that need to be overcome before their full potential can be realized [9].

In this article, we propose a remote pervasive patient health monitoring (PPHM) framework. The proposed framework leverages the combined strong synergy of IoT, CC, and wireless technologies for efficient and high-quality remote patient health status monitoring. The article makes the following contributions:

- A flexible, energy-efficient, and scalable remote patient health status monitoring framework
- A health data clustering and classification mechanism to enable good patient care
- A case study where the capabilities of the PPHM framework are exploited for patients with heart disease
- Performance analysis of the PPHM framework to show its effectiveness

The rest of the article is organized as follows. First, we provide related work. We then present the proposed cloud and IoT integrated remote health status monitoring framework. Next, we

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Jemal H. Abawajy is with Deakin University; Mohammad Mehedi Hassan is with King Saud University.

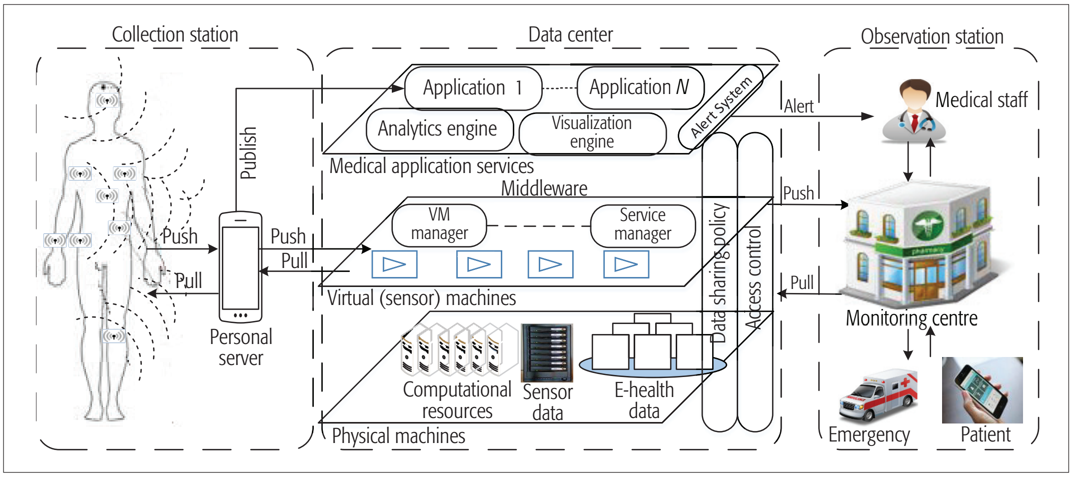

Figure 1. Internet of Things and cloud-based architecture for remote healthcare monitoring.

Continuous monitoring is performed when an intensive monitoring is needed for patients. In this case, sensors continuously collect vital data and send it to the personal server. The on-demand monitoring occurs when a request from any authorized person within the system such as patients, doctors or nurses is generated.

present an ECG process analysis using the proposed monitoring system. We report performance analysis of the PPHM framework. Fifnally, the conclusion is outlined.

Related Work

The question addressed in this article is how to remotely monitor and evaluate the health of patients in the comfort of their own homes. Integrating IoT and CC for patient health and activity monitoring has been an active research area lately. A complex framework that encompasses several heath ecosystems, where data from the sensors is watermarked for security purposes and transmitted to the cloud for feature extraction and classification is discussed in [2]. One-class support vector machine classification is used in the framework to classify an ECG as abnormal or not. A privacy-preserving data collection and secure transmission framework is presented in [6]. BodyCloud [7] is a three-tier integrated software as a service (SaaS)-based cloud and body sensor networks (BSNs) architecture that enables the development and deployment of cloud-assisted BSN applications. A mobile healthcare system for wheelchairs that exploits BoudlyCloud components is discussed in [10]. The framework in [5] integrates TCP/IP and Zigbee for interoperability in the coordinator devices. The framework discussed in [8] is designed to perform diagnosis of chronic illnesses such as diabetes. Patient data are collected through body sensors and stored in the cloud for subsequent analysis and classification. This client-server model framework does not consider energy consumption. In the architecture proposed in [9], patient data is transferred through the home gateway to the cloud, where it is processed and then made available to healthcare professionals or patients. How this is done is not really explained.

Our work is motivated by these previous works and complements them in many ways. As in [7], our PPHM framework is three-tiered with push-pull communication between the three tiers. Thus, in our model, an authorized healthcare professional can request and obtain the real-time data collected by a particular sensor in an IoT subsystem. This capability is generally absent from these works. As in [2], our framework integrates data analytics based on our prior work [11, 13]. Unlike [2], we use data clustering and classification mechanisms to improve classification accuracy. We also consider optimization of the communication and energy consumption at all levels of the system. Unlike the previous studies, we assume that the cloud is used by many competing applications, and proper service provisioning is used to allocate cloud resources to the competing applications.

Remote Health Status Monitoring Framework

This section describes the general three-tier architecture of the proposed PPHM framework shown in Fig. 1. In the following subsections, we explain the major components of the framework.

Observation Station

The observation station consists of an IoT subsystem that is tasked with remote physiological and activity monitoring of patients. The core monitoring infrastructure of the IoT subsystem is the wireless BSNs. This subsystem contains a set of n BSNs, $B = \{b_1, ..., b_n\}$. Each $b_i \in B$ represents a patient and is defined as $b_i = \langle S, P \rangle$, where P is a personal server and $S = \{s_1, ..., s_m\}$ is a set of m energy-constrained lightweight wireless sensor nodes. Each sensor $s_i \in S$ has enough capability to collect patient data, aggregate it, perform basic processing, and transmit it to a personal server for further processing. These sensors can be implantable, worn or attached, to everyday objects such as clothes unobtrusively to gather specific physiological parameters such as a patient's blood sugar levels, blood glucose, capnography (i.e., CO_2 level and breathing), and pulse oximetry and ECG continuously or on demand. Continuous monitoring is performed when intensive monitoring is needed for patients. In this case, sensors continuously collect vital data and send it to the personal server. The on-demand monitoring occurs when a request from any authorized person within the system, such as a patient, doctor, or nurse, is generated.

The personal server provides a link between the IoT subsystem and the cloud infrastructure. The personal server is a dedicated per-patient machine (e.g., a tablet or smartphone) with built-in features such as a GPS module, Bluetooth radio

The cloud also hosts the middleware system, virtual sensors, and application services that allow medical staff to analyze and visualize patients' data as well as to identify and raise alerts when events requiring urgent intervention are observed.

module, and SQLite database. We assume that the personal server can compatibly interact with various local networks such as WiFi and LTE [4]. Each sensor within a given BSN is wirelessly connected via a single hop to a dedicated personal server. We assume that the default communication between the sensor nodes to a personal server is via Bluetooth. The personal server receives a stream of sensor data from the sensors. It performs basic data analysis and aggregation, generating alarm signals, making the data available to the entities subscribed to be notified (e.g., patient), or pushing the data (along with the location of the patient) out to the cloud for further analysis and sharing by healthcare professionals. In order to manage bandwidth and energy consumption, a fuzzy-based data fusion technique that distinguishes and aggregates only the true values of the sensed data [14] is used. This method decreases the processing and transmission of the sensed data as well as removes redundant data, thus minimizing energy depletion while prolonging the network lifetime. In addition to transferring data from the sensors to the cloud, the personal server can possibly receive a request for specific data from cloud applications or an end user.

Data Center Subsystem

The cloud relieves the IoT subsystem by performing heavy functions that require storing, processing, and analyzing the collected patient health data from the IoT subsystem. Cloud storage offers benefits of scalability and accessibility on demand at any time from any place. The healthcare provider data center hosts the cloud subsystem, which delivers storage resources and provides computational capability for analyzing and processing of the collected data. The cloud also hosts the middleware system, virtual sensors, and application services that allow medical staff to analyze and visualize patients' data as well as to identify and raise alerts when events requiring urgent intervention are observed. The major components of the cloud subsystem are described below.

Patient Data Storage: The cloud storage resources are used for long-term storage of patients' medical information (e-Health) and the data from the IoT subsystem (sensory data). E-Health contains the conventional clinical data (e.g., clinic observation and lab test results) while the sensory data contains longitudinal patient data provided by BSNs. Based on the access control configuration, healthcare practitioners or emergency centers can access the stored information without visiting the patient. The physicians, having access to the sensory data along with the e-Health data supported by decision support systems, can improve the quality of patient health in remote locations by making better and quicker prognoses, intervention, and treatment recommendations.

Health Data Sharing Policy (HDSP): One of the aims of the healthcare service providers for collecting clinical data from patients is to share them with authorized healthcare professionals. As data security and privacy are important issues in healthcare systems [2], we use an access control mechanism (e.g., signature or certificate) that ensures only legitimate end users can access the data in the cloud. We also use policy to control the sharing of data. HDSP governs how the patient data is shared among the authorized entities and used to verify the identity of the user with access authority. For instance, the policy can define that access to the sensor reading in the sensor data storage and the corresponding analysis results can only be accessed by the doctors in the neurology department. HDSP also ensures that patient unique identities and associated profiles should be anonymized before the data is shared with other entities such as a research center. In the proposed framework, the data monitoring unit is responsible for setting up the HDSP taking into account regulatory compliance requirements and the need for sharing to provide the best possible care for the patient.

Cloud Middleware: The middleware consists of a virtual machine (VM) manager and a service scheduler, among others. The VM manager is responsible for managing the virtual sensors, which are virtualized counterparts of physical sensors in BSNs, collecting sensor data from personal servers, and storing those data in the "sensor data" store. As compared to the standard cloud workloads such as non-real-time data for scientific computation and storage, the workload from the IoT subsystem is characterized by high inter-arrival rates and highly variant runtimes but with low parallelism. Thus, it becomes important to have cloud resource management and scheduling that can be adapted to handle such different workloads. Thus, service scheduling is necessary to properly schedule many real-time and non-real-time service requests to improve resource usage efficiency. Also, the scheduler performs dynamic load balancing and adaptive resource management in an energy-efficient manner.

Medical Application Services: The cloud hosts various services that process clinical data collected from the IoT subsystem for clinical observation and intervention, and to dispatch ambulances or notify family members of patients. The analytics engine (AE) extracts features from the collected data and classifies the data to assist healthcare professionals to facilitate good patient care. For the healthcare professionals to use the results from the AE to reach accurate and appropriate responses and actions, the output from AE will be used by the visualization engine to make the data accessible to the healthcare professionals in a readily digestible format. The alert system raises alert signals when events requiring urgent interventions are observed. The alarm function generates alerts if the value of the sensed physiological parameters exceeds a predetermined threshold value. For example, an alarm signal is generated when abnormalities such as arrhythmia or hypotension are detected. This capability enables patient health problems to be detected without visiting a doctor, notifying healthcare providers if a check-up is needed, and generating emergency alerts to ambulances.

Observation Station

The observation station is where data-driven clinical observation and intervention take place. At this tier, entities such as healthcare professionals (e.g., doctors), emergency response services, medical research centers, and patients have presence. The monitoring center involves the participation of many healthcare actors, including doctors, patients, and nursing staff, in clinical observation, patient diagnosis, and intervention processes. Thus, all access requests for patient data are managed by the monitoring center. Any authorized user wanting to access the sensor data can do so by issuing a data request to the cloud through the monitoring center. If the requested data is available in the sensor data storage, the data will be returned to the user. Therefore, the healthcare professionals must have appropriate authentication and authorization credentials to access the data.

The framework also allows authorized users or applications to pull any missing or extra data on an on-demand basis from the personal server. The personal server will retrieve data from either its memory or a sensor node and send it to the end user or the application. Entities at this level can subscribe to the data service to be informed automatically when specific data or patterns are observed. For example, patients can subscribe to receive data for the purpose of self-health monitoring. This can happen, for example, after data analytics and health indicators, when the system provides medical advice to the user. In this case, the data is automatically published to the subscribers immediately when it becomes available. The patient can use data such as blood sugar levels to take appropriate actions in case of anomaly detection. Such knowledge-based decisions may lead to reduction in the number of visits to doctors, tests, and hospitalizations. It can also inform caregivers and emergency centers through SMS. The advantage of this service model is less network traffic and power consumption.

Case Study: Congestive Heart Failure

In this case study, we consider a patient suffering from congestive heart failure (CHF) requiring care on a regular basis at her home. CHF develops when the heart's blood pumping ability weakens due to factors such as coronary heart disease, hypertension, and arrhythmia [11]. The cardiac activity of the patient is monitored via ECG, which is a non-invasive diagnostic method for monitoring and detecting a range of heart diseases.

Figure 2 illustrates the proposed framework for remote patient monitoring. In the example, a physician initiates the monitoring and the execution of the data analysis processes. The physician can define the start and end times of the monitoring period. The monitoring center goes through the setup process, which includes confirmation that the requesting agent is an authorized individual, the setup of the personal server that is capable of collecting, aggregating, and sending patient data through the Internet based on patient location (e.g., home, hospital, or outdoors), the registration of the personal server, the initiating doctor, thresholds to be checked for alert initiation, and the exchange of encryption keys between the cloud and the personal server. In addition, the type of monitoring service (continuous or on request) needs to be selected by the physician.

After the setup step is completed, the IoT subsystem starts gathering key physiological parameters and forwarding the data to the personal server, where the data is aggregated and

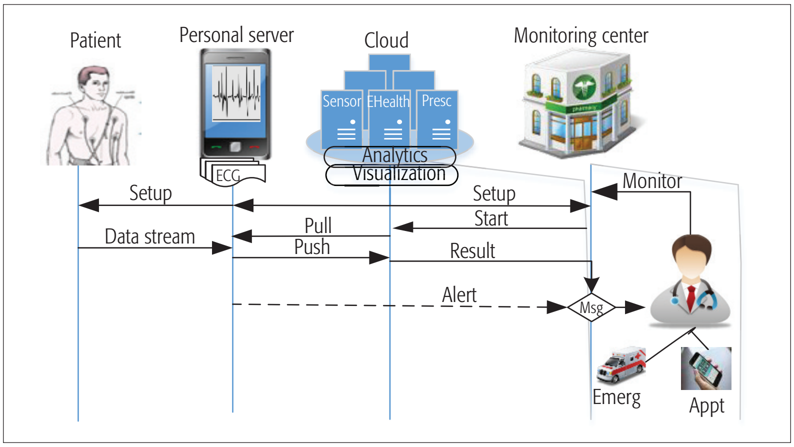

Figure 2. The PPHM framework monitoring process.

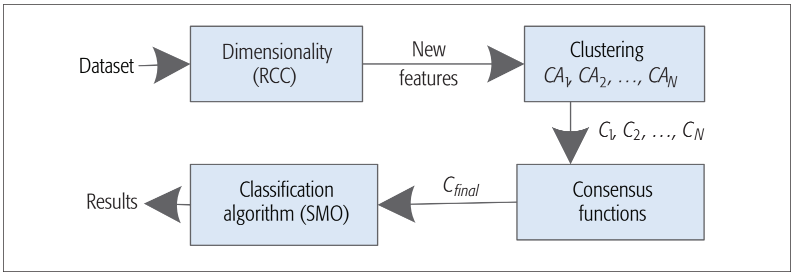

Figure 3. ECG data classification.

relayed to the sensor data storage linked to the patient e-Health records in the cloud system. In conventional settings, the physicians examine the ECG recordings visually for important features. As manual inspection of ECG heartbeats can lead to inaccurate decisions [11], automatic classification of the ECG signals is important for clinical diagnosis of various heart diseases. However, the ECG dataset is highly dimensional, large, and noisy in nature. To address this problem, we use an approach that combines feature reduction, consensus clustering, and classification algorithms for ECG data profiling. Figure 3 shows the components of the multistage system model.

The ECG dataset is processed by the dimensionality reduction algorithm, which is the rank correlation coefficient (RCC) algorithm to obtain fewer features that effectively capture the behavior of the ECG signals. The output from RCC is fed into a set of unsupervised clustering algorithms (i.e., Cobweb, Expectation Maximization, Farthest First, and Simple *K*-Means) algorithms. This step generates a set of *n* independent clusters $C = \{C_1, C_2, C_n\}$. We used the hybrid bipartite graph formulation (HBGF) consensus function to combine the *C* clusters and produce a final consensus cluster (C_{final}). HBGF is based on a bipartite graph, and the C_{final} is determined by the way HBGF partitions all elements of the data set. Finally, we used sequential minimal optimization (SMO) with a polynomial kernel supervised classification algorithm to classify the dataset.

Performance Evaluation

In this section, we evaluate the proposed framework using an emulator-based approach [7, 15] on real ECG signals from the BIDMC Congestive Heart Failure Database (CHFD). The CHFD dataset contains ECG recordings from 15 subjects with severe congestive heart failure. The individual recordings are each approximately 20 h in duration. They contain two main ECG signals, each sampled at 250 samples/s with 12-bit resolution over a range of ±10 mV. As in [15], we use the ECG Sensor Emulator, implemented in Matlab, to generate an ECG data stream by converting each ECG sample from the CHFD dataset to a series of pairs of 16-bit frames and transfer them to the personal server over Bluetooth.

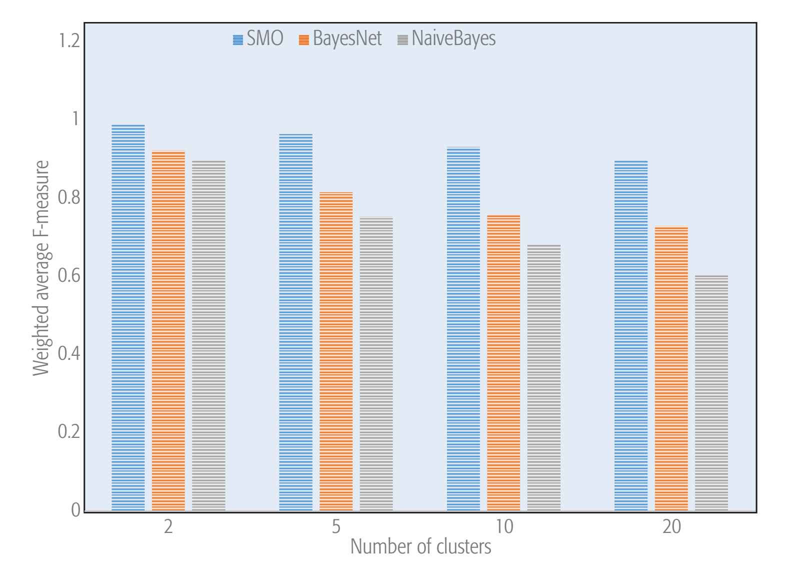

Figure 4. Classification accuracy.

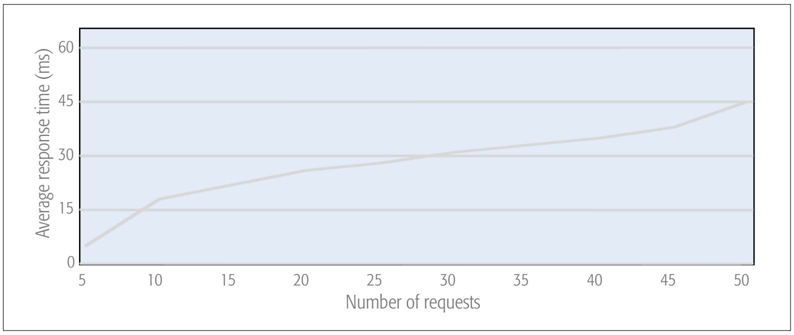

Figure 5. System scalability.

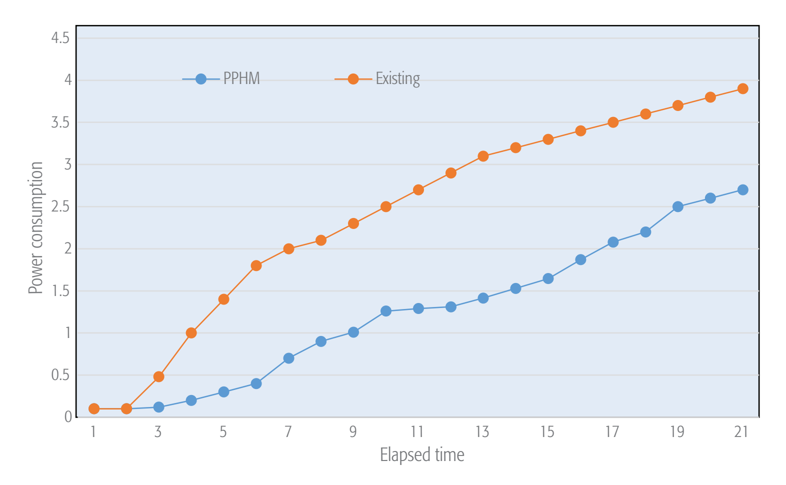

Figure 6. Commutative power consumption.

ECG Classification

We studied the effectiveness of the proposed classification scheme using the weighted average F-measure. We used 10-fold cross validation and compared the SMO-based classification algorithms with the Bayes Network Learning (BayesNet) and Classical Naive Bayes (NaiveBayes) algorithms.

Figure 4 shows the performance (weighted average F-measure) of the three classification algorithms as a function of the number of clusters after their training on the initial consensus clustering data. In [2], the accuracy obtained was 87.7 percent with MIT-BIH database and 90.4 percent with a private database. In our case, we achieved 89.7 percent with 20 clusters and 98.9 percent with 2 clusters. The results establish that our classification algorithms achieve high accuracy with the SMO-based classifier achieving the best results. The result also demonstrates that the SMO-based classifier scales up much better as the number of clusters increases. These algorithms can be used in practical implementations for profiling of highly dimensional, noisy, and large ECG datasets.

Scalability Analysis

To study the scalability of the system, we emulated a set of clients that concurrently transmit sensor data stream as in [7]. We model the request inter-arrival time as a Poisson process, while the service demand is randomly selected between 1 to 5 ms. We repeated the experiment 1000 times and took the average result. Figure 5 shows the average response time as the number of simultaneous requests vary. As the number of requests increase, we can see that the response time increases linearly.

Energy Consumption

In order to study the energy consumption effectiveness of the proposed PPHM framework, we model energy consumption for sensing, computation, and transmission of the messages for a period of time and check the level of the energy usage. We send a b-bit message over a distance d as $((E_{elec} + b) + (\epsilon_{amp} + b + d^2))$ and receive this message as $(E_{elec} + b)$. The E_{elec} = 50 nJ/bit is the energy dissipated to run the transmitter or receiver circuitry, and ϵ_{amp} = 0.1 nJ/bit is the transmit amplifier. The initial energies of each sensor node is fixed at 1.0 J.

Figure 6 shows the cumulative power consumption as a function of the elapsed time. As the existing framework does not deploy any optimizations, it dissipates energy faster than our framework. In contrast, we deploy optimization techniques such as the fuzzy-based data fusion method to manage bandwidth and energy consumption. This method is able to decrease the transmission and the processing of the sensed data as well as remove redundant data, thus minimizing energy consumption while increasing the network lifetime.

Conclusions

In the conventional hospital-centric healthcare system, patients are often tethered to several monitors. In this article, we develop an inexpensive but flexible and scalable remote health status monitoring system that integrates the capabilities of the IoT and cloud technologies for remote monitoring of a patient's health status. Through experimental analysis, we have shown that the proposed framework is scalable and energy-efficient with very high classification accuracy. We believe that the proposed work can address the healthcare spending challenges by substantially reducing inefficiency and waste as well as enabling patients to stay in their own homes and get the same or better care. We are currently implementing the proposed algorithm and testing it in a real-life environment. We are also extending the proposed work to include the privacy and security aspects.

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Biographies

Jemal H. Abawajy [SM'11] (jemal@deakin.edu.au) is a full professor at Deakin University, Australia, where he leads the distributed computing and security research group. He has served over 300 conferences in various capacities and on the Editorial Boards of several journals. He has published more than 300 refereed articles and given more than 50 invited/keynote presentations.

Mohammad Mehedi Hassan [M'12] (mmhassan@ksu.edu.sa) is an assistant professor in the College of Computer and Information Sciences (CCIS), King Saud University (KSU), Riyadh, Kingdom of Saudi Arabia. He has published over 100 + research papers in journals and conferences of international repute. He received the Excellence in Research Award from CCIS, KSU in 2014 and 2015. His research areas of interest are cloud federation, multimedia cloud, sensor cloud, the Internet of Things, big data, and mobile cloud.

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