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Energy efficient fog-assisted IoT system for monitoring diabetic patients with cardiovascular disease

Tuan Nguyen Gia [a,*], Imed Ben Dhaou [b], Mai Ali [c], Amir M. Rahmani [d,e], Tomi Westerlund [a], Pasi Liljeberg [a], Hannu Tenhunen [a]

[a] Department of Information Technology, University of Turku, Turku, Finland
[b] Department of Electrical Engineering, Qassim University, Saudi Arabia
[c] Department of Electrical Engineering, Alfaisal University, Saudi Arabia
[d] Department of Computer Science, University of California Irvine, USA
[e] Institute of Computer Technology, TU Wien, Vienna, Austria

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ABSTRACT

Blood glucose plays an important role in maintaining body's activities. For example, brain only uses glucose as its energy source. However, when blood glucose level is abnormal, it causes some serious consequences. For instance, low-blood glucose phenomenon referred to as hypoglycemia can cause heart repolarization and induce cardiac arrhythmia causing sudden cardiac deaths. Diabetes, which can be viewed as a high-blood glucose level for a long period of time, is a dangerous disease as it can directly or indirectly cause heart attack, stroke, heart failure, and other vicious diseases. A solution for reducing the serious consequences caused by diabetes and hypoglycemia is to continuously monitor blood glucose level for real-time responses such as adjusting insulin levels from the insulin pump. Nonetheless, it is a misstep when merely monitoring blood glucose without considering other signals or data such as Electrocardiography (ECG) and activity status since they have close relationships. When hypoglycemia occurs, a fall can easily occur especially in case of people over 65 years old. Fall's consequences are more hazardous when a fall is not detected. Therefore, we present a Fog-based system for remote health monitoring and fall detection. Through the system, both e-health signals such as glucose, ECG, body temperature and contextual data such as room temperature, humidity, and air quality can be monitored remotely in real-time. By leveraging Fog computing at the edge of the network, the system offers many advanced services such as ECG feature extraction, security, and local distributed storage. Results show that the system works accurately and the wearable sensor node is energy efficient. Even though the node is equipped with many types of sensors, it can operate in a secure way for up to 157 h per a single charge when applying a 1000 mAh Lithium battery.

1. Introduction

Hypoglycemia describes an abnormal phenomenon when the blood glucose level goes below 60 mg/dl. Hypoglycemia causes heart repolarization and may induce cardiac arrhythmia which is one of the primary causes of sudden cardiac deaths [1,2]. According to Centers for Disease Control and Prevention [3], millions of people are affected by arrhythmia. Especially, people with the age of 60 or more are at high risk of arrhythmia or atrial fibrillation (AF). QT-interval lengthening of ECG is a sign of arrhythmia. Recently, research works have proposed the prediction of hypoglycemia by analyzing QT-period and T-Wave [1,4]. Hyperglycemia describes an abnormal high-blood glucose level (e.g. 100–125 mg/dl as pre-diabetes and higher than 126 mg/dl as diabetes). Heart repolarization time is altered by hyperglycemia [5,6]. Similarly, hyperglycemia can be predicted by measuring QT-interval length, QT-interval variability (QTV) and corrected QT interval variability (QTcV). According to WHO, this number increased dramatically from 108 to 422 million during 1990–2014 [7] and is projected to raise up to at two or three times by 2030 [8]. People from any gender and any age can have diabetes. For example, approximately 200,000 people who live in the USA and are under 20 years old have diabetes [9]. Diabetes not only occurs in developed countries but also in developing countries. According to National Vital Statistics Reports (NVSR), diabetes has a rank of 7 among the 15 leading causes of deaths in 2014 [7]. The number of deaths directly caused by diabetes is approximately 1.5 million in 2014 [8]. In addition, diabetes can directly or indirectly cause heart attack, stroke, heart

* Corresponding author.
E-mail address: tunggi@utu.fi (T. Nguyen Gia).

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failure, kidney failure, blindness and other vicious diseases which are primary causes of deaths [10]. Unfortunately, diabetes cannot be cured with the existing knowledge. One of the methods for reducing the serious consequences caused by diabetes is to continuously monitor the blood glucose level and adjusting the insulin level in real-time.

Fall and its consequences cannot be neglected or underestimated because they might be the cause of serious injuries and traumas. For instance, bone fracture, broken knee, neck fracture, head bruises and head traumas can be caused by falls [11,12]. The injuries require a long period of time to be healed and fully recovered. Correspondingly, they cause significant costs and reduce the quality of life [13]. However, merely 50% of the falling cases are reported and in-time aided. Unreported cases might cause difficulty and complication in treatments later.

Diabetes, cardiovascular diseases, fall and old people often have some relationships. Diabetes has been identified as a risk factor for falls [14,15]. For example, people who are over 65 years old are like to have diabetes, cardiovascular diseases and fall more often. According to statistics, more than 25% of people who are over 65 years old have diabetes and more than 30% of these people fall every year with hazardous consequences [11,16]. In addition, more than 68% of these people having diabetes die from cardiovascular diseases [15]. Therefore, it is required to have a system which can both monitor diabetes, ECG and inform abnormalities (e.g., a fall, very low or high glucose level, and abnormal heart rate) in real-time without interfering the patient's daily activities.

Internet of Things (IoT) can be considered as one the most suitable candidates for addressing the target. IoT can be expressed as a platform where physical and virtual objects are interconnected and communicate together. IoT consisting of many advanced technologies such as sensing, sensor network, Internet and Cloud computing is capable of providing remote health monitoring in real-time while the quality of life can be maintained. Via IoT systems, collected data is stored in Cloud servers. Therefore, real-time data and the historical data can be accessed remotely in anytime. In addition, IoT systems are able to perform real-time responses or actions. For example, an insulin pump of IoT systems can automatically or be remotely controlled for injecting insulin into the patient's blood when the blood glucose is high.

Although glucose monitoring IoT systems have advantages such as remote real-time monitoring and global data storage, they have limitations. For example, most of them are not secured because the data transmitted over the network is not protected and encrypted. The transmitted data can be listened and altered by unauthorized parties [17]. Furthermore, many health monitoring IoT systems do not provide advanced services such as distributed local storage, push notification, and data analysis. Correspondingly, incorrect diagnosis and treatments of diseases may occur when both contextual data and patient's activity status are not analyzed altogether with e-health data. As a result, caregivers such as doctors might not be able to save a patient life. Most of the existing IoT health monitoring systems do not consider the close relationship of diabetes, cardiovascular disease, and fall cases.

A proper approach to solve the challenges in IoT systems is to enhance sensor nodes and apply an extra layer named as Fog between gateways and Cloud servers. Fog layer is run on the top of smart gateways to provide advanced services for enhancing the quality of services. For example, Fog helps to save network bandwidth between gateways and Cloud servers by processing and compressing data [18,19]. Furthermore, Fog helps to reduce the burdens of Cloud servers by pre-processing data at smart gateways. Fog provides distributed local storage for temporarily storing data. In addition to mentioned services, Fog helps to facilitate many other advanced services such as system fault detection, database synchronization, interoperability, mobility-awareness [20]. Moreover, Fog creates a convergent network of interconnected and intercommunicated gateways, that helps to overcome service interruption. For instance, when a connection between a smart gateway and Cloud servers is interrupted, real-time data streaming is still maintained. In this case, data is sent to Cloud servers via adjacent smart gateways which are directly connected and geographically close to the "interrupted" gateway. With the benefits of advanced services, Fog not only solves many challenges of IoT systems but also enhances the quality of services dramatically.

In this paper, a smart IoT system based on Fog for remote healthcare monitoring is introduced. For improving the accuracy of diseases analysis and diagnosis, the system monitors not only e-health data such as blood glucose, ECG, patient's movement and body temperature but also contextual data such as room temperature, humidity, and air quality. The system is secured with cryptography algorithms for protecting the collected data. Particularly, data is encrypted at sensor nodes before being transmitted and decrypted at smart gateways. The system with the Fog layer offers advanced services such as interoperability, distributed local storage, data processing (i.e., QT intervals extracted from an ECG waveform, activity status categorization, and fall detection via lightweight algorithms). Last but not least, the enhanced energy-efficient sensor node for monitoring vital signals is presented. The main contributions of this work are summarized as follows:

- A complete implementation of a Fog-assisted IoT system for monitoring diabetes patients with cardiovascular diseases
- Light-weight algorithm at Fog-assisted gateways for ECG feature extraction
- Light-weight algorithm at Fog-assisted gateways for activity status categorization and fall detection
- Designing and implementing energy efficient wearable sensor nodes for collecting ECG, glucose, body temperature and motion-related data
- Analysis of e-health data in different scenarios and patient's activities

The rest of the paper is organized as follows: Section 2 includes related work and motivation for this work. Section 3 provides an overview architecture of the health monitoring IoT system having Fog assistance. Section 4 emphasizes on Fog services such as the algorithm for extracting QT intervals from an ECG waveform, fall detection, and activity status categorization. Section 5 presents test-bed and the system implementation. Section 6 provides insights about experimental results. Finally, Section 7 concludes the work.

2. Related work and motivations

Many efforts have been made for proposing real-time and remote health monitoring IoT-based systems. In [21,22], an ECG monitoring IoT-based system using 6LoWPAN is proposed. The system consists of smart gateways and energy efficiency sensor nodes. In [23,24], authors present IoT systems for fall detection. The systems use wearable sensor nodes for collecting 3-dimensional (3-D) acceleration and 3-D angular velocity. The systems with smart gateways offer push notification services for informing a fall to caregivers. In [25], authors present an IoT system with a smart gateway for e-health monitoring. The gateway supports interoperability with Bluetooth Low Energy (BLE), Wi-Fi, and IPv6 over Low-Power Wireless Personal Area Networks (6LoWPAN). In addition, the gateway provides many advanced services such as data compression, data storage, and security. In [26], authors present a glucose monitoring IoT-based system which shows some levels of energy efficiency by applying 6LoWPAN and RFID. The system can distinguish non-fasting and fasting cases for an accurate

diagnosis. In [27], authors propose an IoT system for non-invasive glucose level sensing. The system uses a laptop as a gateway for receiving data from 6LoWPAN nodes and sending the data to Cloud servers. In most of the discussed work, security is not attentively considered. Especially, the connection between sensor nodes and the smart gateway is not fully protected. Some of the works provide smart gateways. However, services provided at the smart gateways are limited. Some of the works do not support interoperability which limits the flexibility and ubiquity of the health monitoring systems.

Other works [28,29] consider high levels of security for health monitoring IoT systems. The connection between sensor nodes and smart gateways are secured by light-weight cryptography algorithms. However, the energy efficiency of sensor nodes is not attentively considered.

Recently, researchers have proposed health monitoring IoT systems with Fog computing. The Fog-based systems have advantages such as bandwidth saving, energy efficiency, and a high level of security. In [30], authors apply a smart gateway and Fog computing into an ECG monitoring IoT system. The system provides many services such as categorization, push notification and distributed local storage. In [31], authors propose an IoT system with Fog computing for continuous glucose monitoring system. The system uses a mobile-based gateway for processing and analyzing data. When the smart gateway detects abnormalities such as too low or too high blood glucose level, it sends push messages for informing medical doctors in real-time. In [18,19], authors propose Fog approaches for ECG monitoring systems. The systems can extract ECG features at Fog and achieve some levels of energy efficiency at sensor nodes. In [32,33], health monitoring IoT systems with Fog computing are proposed. These systems provide many advanced Fog services such as data analysis, data fusion, distributed local data storage, and data compression. By using a web-browser, real-time ECG data can be remotely and real-time monitored. In [34], authors propose a Fog approach for enhancing telehealth big data. The system analyzes ECG data for finding similar patterns. In [35], authors present a Fog approach for a fall detection IoT system. Fog computing and Cloud servers run the U-fall algorithms for detecting fall automatically in real-time. In [36], a Fog approach for a medical warning system is proposed. ECG is analyzed at Fog for early-detecting patient deterioration. In [37] Fog computing for reliable e-health applications (i.e., human fall detection) is applied. The system has both e-health and contextual sensor nodes which are built from general purpose devices (e.g., Arduino Uno and Lilypad). These sensor nodes transmit the collected data to a computer for processing. In [38], authors present a Fog-based fall detection system. In the system, a set of fall detection algorithms is developed and proposed. In the system, tasks are split between edge devices and Cloud servers to achieve real-time analysis. In [39], authors present a Fog-based system for monitoring mild dementia and chronic obstructive pulmonary disease (COPD) patients. The system consists of e-health, contextual nodes and Fog nodes. An environment node of the system based on Arduino Uno collects temperature, humidity, gas, CO2, and oxygen information while e-health node acquires 3-D acceleration. The data is sent via Zigbee. The Fog node is responsible for real-time processing and notification. In [40], authors claimed that cloud-based healthcare services with intermediate Fog nodes can help to improve quality of healthcare. For instance, health insights can be acquired accurately while information privacy is protected. The Fog node running a privacy middle-ware helps to reduce the burden of IoT sensor nodes. Accurate results provided by the system can benefit both caregivers and end-users. In [41], authors propose a system for monitoring and adjusting the oxygen level in real-time for obstructive pulmonary disease patients. The system is able to acquire different types of data including both contextual and e-health data. In addition, the system is equipped with a Fog-to-Cloud (F2C) service to process the data and adjust an oxygen level in real-time.

Although the mentioned Fog-based approaches provide advanced services for enhancing health monitoring systems, none of them consider all aspects of sensor node's energy efficiency, security, and the relationship of diabetes, cardiovascular disease and patient fall together. Energy efficiency is a vital characteristic of healthcare IoT systems. When a sensor node is not energy efficient, it can cause service interruption which is one of the reasons for reducing the accuracy of disease analysis. When the system is not secured, patient's information can be stolen or the system can be instructed for doing unacceptable actions. Disease analysis and diagnosis might be inaccurate when standalone e-health data is used without considering contextual data or activity status. For instance, heart rate during sitting and training is different. In this paper, we propose an IoT system with Fog computing for health monitoring. The system not only monitors e-health data (i.e., blood glucose, ECG, and body temperature), daily activity, and contextual data (i.e., room temperature, humidity, air quality) but also provides advanced services for improving the accuracy of disease analysis and informing abnormalities (i.e., hypoglycemia, hyperglycemia, and cardiac disease). In addition, many techniques and Fog approaches are applied to achieve a high level of energy efficiency while the connection between sensor nodes and smart gateways is protected by an AES algorithm.

3. Architecture

The architecture of the proposed system shown in Fig. 1 has 3 layers including sensor node layer, Fog computing layer consisting of Fog-assisted smart gateways, and Cloud servers with end-user terminals. Each layer is discussed as follows:

3.1. Sensor layer

Sensor layer includes different types of sensor nodes such as contextual sensor nodes, e-health sensor nodes, and actuator nodes. Contextual sensor nodes can be fixed at a single room for gathering contextual data from surrounding environments such as a room temperature, humidity, time, location and air quality. The contextual data plays an important role in achieving accurate analysis. For example, human pulse rate is likely to increase when the temperature rises. In [42], from the experiments with more than 30 thousand children, authors showed pulse rate increases more than 20 pulses when the temperature rises from 35 to 40 Celsius degrees.

E-health sensor nodes can be categorized into different types depending on the given health monitoring application. In this paper, three types of e-health sensor nodes such as low data rate sensor nodes, high data rate sensor nodes and hybrid sensor nodes equipped with both low and high data rate sensors. Low data rate sensor nodes can be used for acquiring blood glucose, body temperature, and humidity. High data rate sensor nodes can be used for collecting ECG and body motion (e.g., acceleration and angular velocity). Hybrid sensor nodes equipped with both low and high data rate sensors can be used for collecting all types of data such as ECG, body temperature, glucose, humidity, and body motion.

Actuator nodes are used for controlling actions related to health or the surrounding environment. Actuator nodes often receive instructions from a smart gateway. For example, an atmosphere controlling actuator can adjust a room's temperature and humidity.

The collected data from sensor nodes is sent to smart gateways via one of several wireless protocols. A choice of a specific

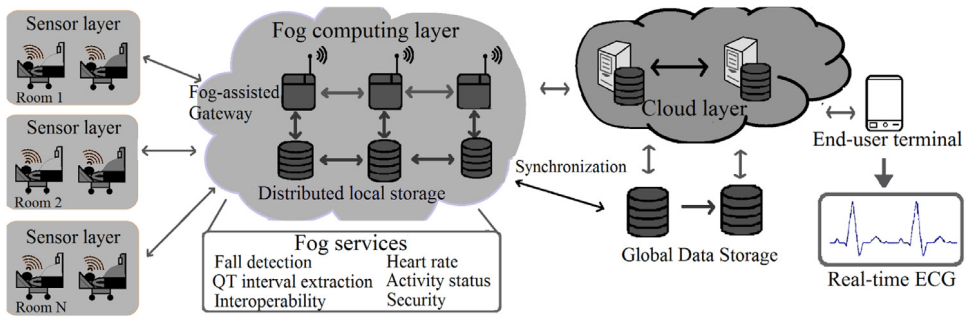

Fig. 1. Architecture of Fog-assisted IoT system for monitoring diabetes patients with cardiovascular disease.

wireless protocol depends on the application's requirements. For example, Wi-Fi is used for high data rate monitoring applications (e.g., 8-channel EMG monitoring in which each channel collects 1000 24-bit samples/s [43,44]). Bluetooth Low Energy (BLE) or IPv6 over Low-Power Wireless Personal Area Networks (6LoWPAN) is used for low data rate health monitoring applications (1-channel ECG monitoring in which each channel collects 125 16-bit samples/s [21,22]). In the proposed system, an nRF protocol, which is ultra low power 2.4 GHz ISM band wireless protocol, is utilized because of its flexibility of data rate support and energy efficiency [45]. The nRF protocol supports data rates of 250 kbps, 1 Mbps, and 2 Mbps. The collected data can be kept intact or pre-processed before being transmitted. Particularly, some of the data (i.e., body temperature, and blood glucose) can be filtered with light-weight filters based on threshold. For instance, a human body temperature cannot be higher 47 Celsius degrees. This value can be used as a threshold value. When a measured sample value is higher than this threshold and the sample value is different than the historical values which were measured in a minute before. The sample is considered as dummy data and it is eliminated. When the sample value is similar to the historical values. The push notification message, which inform the abnormal case such as extremely high body temperature or malfunctioned body temperature sensors, will be sent to administrators via gateways and Cloud. Similarly, 400 mg/dl is used as a threshold value for blood glucose. In other cases, data (i.e., ECG, 3-D acceleration, and 3-D angular velocity) is kept in tact and sent to Fog-assisted smart gateways which perform heavy computational tasks such as wavelet transform and ECG feature extraction [18,19]. For providing some levels of security, data can be encrypted at sensor nodes before being sent to Fog-assisted smart gateways which decrypt the data and perform heavy processing.

3.2. Fog computing layer consisting of fog-assisted gateways

Smart gateways can be fixed or movable depending on the given application. In many health monitoring applications in hospitals, fixed gateways are more preferred because they can use power and Ethernet from wall sockets. Accordingly, fixed gateways can serve many sensor nodes simultaneously and offer advanced services running heavy computational algorithms whilst movable gateways are not capable due to limited battery capacity. In addition, fixed gateways are more secured because they are kept intact and can perform advanced security algorithms.

In addition to conventional tasks of receiving and transmitting data, Fog-assisted smart gateways proffer many advanced services for enhancing the quality of healthcare services. Some of the Fog services are distributed local storage, data compression, localhost with user interface, categorization service, and push notification.

Distributed local storage often consists of synchronized and intact databases. The synchronized database stores real-time contextual and e-health data while the intact database stores data used for algorithms, services and the system's configurations such as username and password and algorithm's parameters. The synchronized database is synchronized with Cloud servers' database while data in the intact database is only updated by system administrators. Due to the limited storage of the synchronized database, the oldest data is purged for storing incoming data.

Data compression helps to save network bandwidth. Although compressing and decompressing cost some resources and latency, they do not affect the performance of other services and only increase the total latency slightly [25].

Categorization service is used to categorize local users and external users. Particularly, the categorization service scans Wi-Fi devices around smart gateways. As a result, local devices are stored in smart gateways' database. When a user tries to connect to smart gateways, the system checks the database. If the user is a local user, the smart gateways send real-time data directly to the user's terminal without going through Cloud servers.

Push notification is one of the most important services in Fog. Push notification is used for informing abnormalities in real-time to responsible people such as system administrators or caregivers.

These services are explained in detail in our previous works [32,30,33]. Although these services are not the main focus of this paper, they are still implemented in the system.

In addition to mentioned services, there are vital services such as data analysis, data processing, interoperability, and security. Detailed information of these services is discussed in Section 4.

3.3. Cloud layer with end-user terminal

Cloud layer provides many benefits such as centralized global storage, scalability, data security and data processing. Heavy computational tasks, which cannot be run at Fog, can be processed smoothly in Cloud servers which are the core of the Cloud layer. For example, Cloud servers support modern machine learning services with pre-trained models. In addition, Cloud servers support powerful search, discovery and image analysis. E-health and other related data (e.g., records of patient's health status) can be stored at Cloud servers. Different technologies (e.g., WebSockets and JSON) can be installed at Cloud for hosting a comprehensive website showing real-time data in both textual and graphical interfaces [46,47]. Furthermore, Cloud servers support push notification sending the instant messages to an end-user in real-time. In the proposed system, push notification is used for informing abnormalities (i.e., related to patient health and the system's technical problems) to responsible people such as caregivers or system administrators. End-users can use terminals such as smart phone's app or web browsers to access both real-time data and the historical data. In addition, end-users such as caregivers can provide instructions or advice via the terminals.

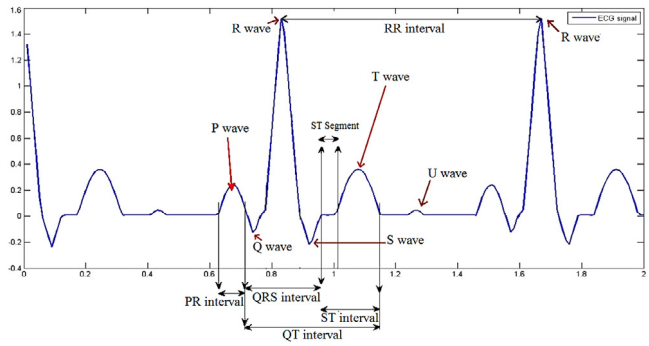

Fig. 2. ECG signal generated using Matlab (Ideal).

4. Fog services

As mentioned, smart gateways in Fog computing can offer many advanced services (e.g., localhost, categorization, and push notification) and thereby potentially enhance the quality of healthcare services. In this paper, interoperability, security, data processing are investigated and explained as follows:

4.1. Data processing

Data processing and data analysis in Fog-assisted smart gateways play important roles in health monitoring systems. They not only help to reduce the burden of Cloud servers but also help to extract important information which can be used for real-time critical decision making and push notification. In this paper, heart rate, QT intervals, corrected QT intervals are extracted from an ECG waveform. The extracted information combined with other e-health data such as blood glucose level, body temperature, and body motion is used for detecting hypoglycemia and hyperglycemia in real-time.

4.1.1. Heart rate and the QT interval extraction algorithm

ECG can be defined as a periodic signal in which each normal ECG waveform represents the electrical events in one cardiac cycle. A normal ECG waveform, shown in Fig. 2, often consists of several waves named as P, Q, R, S, T, and U. If the baseline of the ECG is zero, the three waves P, R, and T often have positive peaks whereas the waves Q and S often have negative peaks.

From an ECG signal, heart rate can be calculated based on the formula: *Heart rate* = 60/*RR interval* [48]. *RR interval* can be easily calculated since R peaks have the highest amplitude among all waves.

Peak detection can be computed using a linear time algorithm that seeks the determination of local extreme. The algorithm to determine the QT-period starts by first locating the lowest interval I_P in which the P-wave reaches its maximum. Then, the same procedure is applied to compute I_P, I_R, I_S and I_T, where the subscript in I designed the type of the wave. The QT-length is then computed using $I_{QT} = I_R + I_Q + I_S + I_T$. The pseudo-algorithm to compute the lowest interval in which a function $f(x)$ reaches its local maximum is shown in Algorithm 1. The algorithm takes two inputs: $x_i = f(t_i)$, where t_i is the instant of time t_i. The algorithm is a stream type, consequently, does not consume memory which makes it suitable for tiny devices.

When QT interval is extracted, corrected QT (QTc) interval can be easily calculated by one of the formulas shown in Table 1. Currently, Bazett's QTc (QTcB) is used as a clinical standard but authors [54] showed that Fridericia's QTc (QTcFri) might become the next clinical standard replacing for QTcB. In this paper, Bazett's QTcB is applied for the experiments.

Algorithm 1 Algorithm to compute local maximum of a function $f(x)$

procedure MAX-ALGORITHM(x_i, t_i)

  if ($x_{i-1} = 0$ and $x_i > 0$) **then**
    $I_1 \leftarrow t_i$
    $M \leftarrow x_i$

  else if ($I_1 \neq 0$ and $x_i > 0$) **then**
    $M = Max(x_i, M)$

  else if ($I_1 \neq 0$ and $x_i = 0$) **then**
    $I_2 \leftarrow t_i$
    break

  return M, $[I_1, I_2]$
where x: value of ECG
t: specific time(s)

4.1.2. Activity status categorization and fall detection algorithm

It is inaccurate to analyze only ECG without considering an activity status because ECG signals change dramatically based on the current activity status. For example, ECG of a person during resting and running is different. Therefore, ECG and activity status must be monitored and analyzed simultaneously.

Activity status representing daily physical activities of a person can consist of three primary groups such as non-moving/resting, walking, and training exercises. Each group can have many activities (e.g., sleeping, lying, standing and sitting belong to a non-moving/resting group or running, push up, weight lifting and other heavy activities belong to a training group). Activities belong to the same group have similar effects to the ECG waveform. Miao et al. [55] show that ECG of a person during standing and sitting are almost similar. Therefore, the paper only focuses on standing, walking and running where each activity represents for each group of three mentioned groups, respectively.

A person's activity status can be detected by using camera or wearable motion sensors. In this paper, wearable motion sensors are used because it does not limit a person's activities. In addition, wearable motion sensors can be used to detect a human fall [56,23]. A person's activity status and a human fall are detected by the algorithm shown in Fig. 3.

The algorithm includes many steps such as the acquisition of 3-D acceleration and 3-D angular velocity, data filtering and fall detection. The algorithm uses both 3-D acceleration and 3-D angular velocity because according to Gia et al. [56], they help to improve the accuracy of a fall algorithm. Similar to ECG signals, motion-based signals are affected by surrounding noise. Therefore, noise must be removed by using filters (e.g., moving average and 50 Hz low pass) to achieve a high quality of signals. The filter data is used to calculate activity-related parameters by the following formulas [56]:

$$SVM_i = \sqrt{x_i^2 + y_i^2 + z_i^2} \tag{1}$$

$$\Phi = \arctan\left(\frac{\sqrt{y_i^2 + z_i^2}}{x_i}\right) * \frac{180}{\Pi} \tag{2}$$

SVM: Sum vector magnitude
i: sample number
x,y,z : accelerometer value or gyroscope value of x, y, z axis
Φ : the angle between y-axis and vertical direction

Table 1
Formulas for calculating corrected QT interval.

Algorithm	Formula
Bazett (QTcB) [49]	$QTc = QT / (\sqrt{RR})$
Fridericia (QTcFri) [50]	$QTc = QT / (\sqrt[3]{RR})$
Framingham (QTcFra) [51]	$QTc = QT + 0.154 \text{ x } (1 - RR)$
Hodges (QTcH) [52]	$QTc = QT + 0.00175 \text{ x } ([60 / RR] - 60)$
Rautaharju (QTcR) [53]	$QTc = QT - 0.185 * (RR - 1) + k$ (k = +0.006 s for men and +0 s for women)

The calculated parameters are compared with a first set of thresholds including activity status categorization threshold and fall detection threshold. For example, activity status categorization threshold consists of 1.2 g and 30 deg/s for 3-D acceleration and 3-D angular velocity, respectively. For detecting a human fall, the first fall detection threshold is 1.6 g and 100 deg/s for 3-D acceleration and 3-D angular velocity, respectively. If the collected data surpasses the first set of thresholds, they are marked as "possibility" data and they are compared with both the second set of thresholds and the historical data. For instance, 1.6 g and 100 deg/s can be used as the second activity status categorization thresholds while 1.8 g and 130 deg/s can be used as the second fall detection thresholds for 3-D acceleration and 3-D angular velocity, respectively. If one of the values surpasses the second fall detection thresholds, a human fall is detected. Simultaneously, the activity status is detected based on the number of values surpassing the first and second activity status categorization threshold. In most of the cases, motion data only surpasses the first activity status threshold when a person is walking. When the person is running, the number of values which are higher than the second activity status threshold is large. The results of comparing the data with the history data help to categorize activity status more accurately. For instance, some periods of the 3-D acceleration should have a similar pattern (i.e., rising up to peak then decreasing) when a person walks or runs. In addition, the results help to detect the malfunctioned sensors. If one of the sensors (accelerometer or gyroscope) and its historical data do not provide the expected values (i.e., 1 g and 0 deg/s for acceleration and angular velocity, respectively when standing or lying in bed), the push notification service is triggered.

4.2. Interoperability

In general, most of the traditional monitoring systems merely support a specific type of sensor nodes such as Wi-Fi-based node for EMG monitoring [43], 6LoWPAN-based node for ECG monitoring [21,22], classic Bluetooth-based node for ECG, EMG monitoring [44] or BLE-based node for human fall detection [23]. Some other systems can support some of the wireless communication protocols such as Wi-Fi and BLE [25]. These systems are not suitable for sensor nodes using other communication protocols such as LoraWan, Zigbee or nRF. Fog computing with its capability offers interoperability to solve these challenges. The interoperability is a capability of supporting not only sensors from different manufacturers but also different communications protocols including wire and wireless protocols. For example, Fog-assisted smart gateways can support Ethernet, Wi-Fi, classic Bluetooth, BLE, nRF, and 6LoWPAN. Depending on applications, other wire or wireless communication protocols can be added into Fog-assisted smart gateways. For instance, LoraWan can be added for supporting long-range distance related applications. When the new hardware (i.e., LoraWan chip) is added to a smart gateway, the operating system of the gateway automatically detects a new device or component. A new thread can be created for transmitting the data via the added component. Sensor nodes in the Fog-based system can work both independently and cooperatively. The sensor nodes can communicate with each other via Fog-assisted smart gateways. In this work, smart gateways support Wi-Fi, BLE, Ethernet, and nRF.

4.3. Security with lightweight cryptography

In health monitoring IoT systems, the connection between sensor nodes and gateways is often the most vulnerable part of the system. The main reason is that the sensor nodes are wearable and resource-constrained devices. Therefore, they cannot run complex security algorithms. Even though complex security algorithms can be run successfully at sensor nodes, they are not applied because latency requirements of the system might be infringed and their battery is depleted. In many IoT systems [24,23,56], raw data is often transmitted for saving sensor nodes' battery life. This approach is dangerous because data can be listened by unauthorized parties. In the worst case, they can instruct commands to cause a harm to a patient. For example, Klonoff [57] uses his software to steal the security credential of the glucose monitoring system. As a result, he has a full control to an insulin pump. In order to avoid such cases, lightweight security algorithm must be run at sensor nodes. The algorithm must provide some levels of security while sensor node's battery life cannot be reduced significantly. In the paper, the AES algorithms [58] are applied. The AES algorithm consists of four basic primary operations (i.e., SubBytes, ShiftRows, MixColumns, and AddRoundKey). Each sensor node or a group of sensor nodes has its private keys for encrypting the data while a gateway has all private keys of all sensor nodes and groups of sensor nodes. The keys are hard-coded in the sensor node's firmware and their length can be 128, 192 or 256 bits. In detail, each sensor node has three different private keys where each private key has an ID and is used during a period of time (e.g., 1 h). Before a new key is applied, the sensor node sends messages to inform a corresponding gateway about the key ID. At a smart gateway, the encrypted data received will be decrypted by the correct private key which has been retrieved from a table of all private keys based on the received ID.

5. Test-bed and system implementation

A complete IoT-based system with Fog computing for continuous glucose, ECG, body temperature and body motion monitoring is implemented. The system includes 4 smart gateways, 6 contextual sensor nodes, 4 e-health sensor nodes, Cloud servers, and end-user terminals such as mobile apps. Two gateways are placed in two adjacent rooms while other two are placed at corridors. These gateways are connected to the Internet via Ethernet cables and supplied with power from wall sockets. Each of the rooms has 3 contextual sensor nodes placed at middle, top and back corners of the room. Each e-health sensor node is attached to a chest of volunteers who are about 30 years old and healthy male and female people. The e-health sensor node collects ECG data via electrodes placed at left arm, right arm, and left leg. The experimented rooms are office rooms consisting of computers and furniture such as tables and chairs. The detailed setup is shown in Fig. 4. Detailed information of the system's components are explained as follows:

5.1. Sensor layer implementation

The system has two types of sensor nodes consisting of contextual sensor nodes and e-health sensor nodes. Each sensor node has

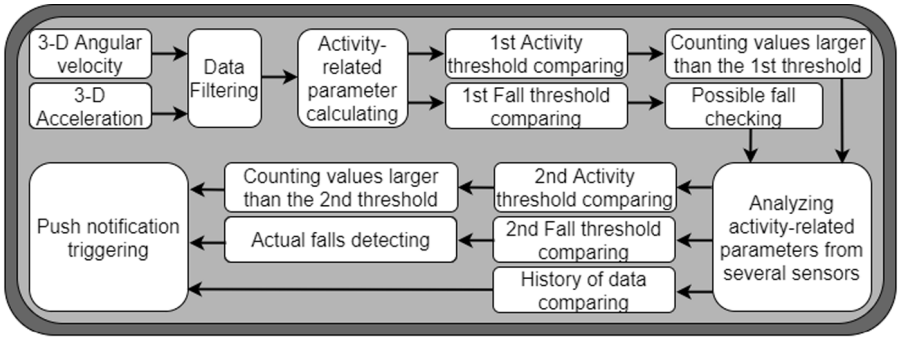

Fig. 3. Activity status and fall detection algorithm.

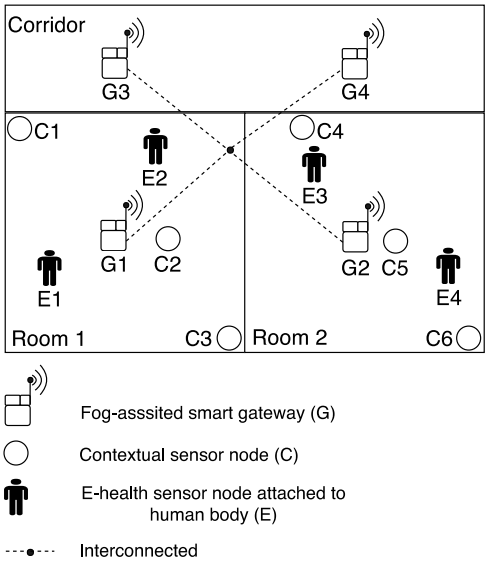

Fig. 4. Test-bed scenario.

five primary components including microcontroller, sensors, energy harvesting unit, power management unit and wireless communication chip. These sensor nodes are discussed in detail as follows:

An ultralow power ATmega328P-8-bit AVR microcontroller is used in sensor nodes. The microcontroller flexibly supports different frequencies (e.g., up to 20 MHz) and various sleep modes for saving energy. In the proposed system, a sensor node merely performs simple computational tasks whilst heavy computational tasks are processed at Fog. Therefore, the sensor node does not need to run at a high clock frequency for saving energy consumption. In the implementation, 1 MHz clock frequency is applied to all sensor nodes.

The microcontroller supports different communication interfaces such as SPI, I2C, UART and many GPIO ports (i.e., digital and analog ports). Correspondingly, it can connect to various sensors and components produced by different manufacturers. Furthermore, the microcontroller has 1 kB EEPROM and 2 kB internal SRAM. Hence, it is capable of supporting many libraries for collecting data from different sensors. In [56], authors show that SPI is more energy-efficient and has a higher bandwidth than other interfaces. Therefore, SPI is used in most of the cases such as the connection between the microcontroller and other components (i.e., wireless communication chip and sensors). In case of unavailable SPI, I2C is preferred.

Contextual sensor nodes are equipped with BME280, SNS-MQ2, SNS-MQ7, SNS-MQ135 for collecting room temperature, humidity, and air quality levels. DHT22 is a small size humidity and temperature sensor which outputs the calibrated digital signals. With a high operating range (i.e., 0%–100% for humidity and −40–80 Celsius degrees), the sensor can operate in harsh environments. The sensor has a high resolution (0.1% RH for humidity and 0.1 Celsius for temperature) and it is accurate (e.g., +−2%RH and +−0.5 Celcius). SNS-MQ2, SNS-MQ7, and SNS-MQ135 are air sensors for collecting LPG, propane, hydrogen, methane, CO, NH3, NOx, alcohol, benzene, smoke, CO2 from the air. These contextual sensor nodes are fixed in a room. Therefore, the contextual sensor nodes can use power from a large capacity battery (e.g., 3.7 V 10 000 mAh Lithium battery having a size of 5 x 120 x 90 mm) or from a wall socket with a voltage adaptor. The detailed information of power consumption of these contextual sensor nodes is presented in Section 6.

E-health sensor node can be categorized into low data rate, high data rate, and hybrid nodes where hybrid node consists of both low and high data rate sensors. Low data rate nodes are equipped with a glucose sensor and a body temperature sensor. The glucose sensor includes an implantable sensor under a patient's skin and a transmitter placed on a top of the skin. In the implementation, the transmitter is connected to the microcontroller via SPI. The glucose sensor collects glucose level every 5 min as the glucose level does not change rapidly. Similarly, the body temperature sensor (i.e., BME280 produced by Bosch) is connected to the microcontroller via SPI. The temperature data is collected every 2 min.

High data rate e-health sensor nodes are equipped with a motion sensor and an ECG analog front-end. A motion sensor (i.e., MPU-9250) is an ultralow power sensor for collecting 3-D acceleration, 3-D angular velocity, and 3-D magnetism. The data rate of the motion sensor is 50 samples/s. The low-power ECG analog front-end can be TI ADS1292 or AD8232. In the implementation, a data rate of 125 samples/s is used.

A power managing unit is a low-power Schmitt trigger based circuit having several super-capacitors. The power managing unit can detect the energy level of the battery, power, and current via INA226 which is a current shunt and power monitor produced by TI.

The wireless communication chip is nRF24L01 which is an ultralow power RF transceiver supporting many-to-many communications. The nRF24L01 chip supports up to 2 Mbps. However, 250 kbps is used for saving energy consumption. The chip can run with low-power, average-power or maximum power. In this paper, it is configured to run at low-power mode and is connected with the microcontroller via SPI.

5.2. Smart gateway and fog services implementation

A smart gateway of the system is built with Pandaboard which has a 1.2 GHz dual-core Arm Cortex microprocessor and 1 GB low-power DDR2-RAM. Pandaboard supports several communication

interfaces such as Wi-Fi, Bluetooth, and Ethernet by built-in components. In addition, it supports a 32 GB SD-card which can be used for installing embedded operating systems. In the implementation, a lightweight version of Ubuntu based on Linux is used. Many services such as security (AES), data decompression, data processing and data analysis have built on the operating system.

For providing interoperability, several wireless communication components are added into Pandaboard. To receive data from the sensor nodes which are equipped with nRF, an nRF24L01 chip is connected to Pandaboard via SPI. The nRF24L01 chip in the gateway is similar to the nRF24L01 chip used in sensor nodes except that it has some extra circuits and uses a large external antenna. Using a large antenna costs higher energy consumption, but it increases the quality of collected signals. For supporting 6LoWPAN, a composition of a CC2538 module and a SmartRF06 board is added into Pandaboard. The detailed information of the connection can be seen in our previous works [21,22]. These components are connected to Pandaboard via Ethernet and USB ports because Ethernet can provide high transmission bandwidth. To support several BLE sensor nodes, the smart gateway can be equipped with BLE components (i.e., CYBLE-202007-01 provided by Cypress Semiconductor). The number of added BLE components depends on the available UART ports of Pandaboard. However, these UART ports are limited. To overcome the issue, an FTDI chip and an ATmega328P microcontroller are added to Pandaboard. These components can facilitate 7 BLE components which are connected via software-based or hardware-based UART. When the number of BLE sensor nodes is larger, more components can be added to Pandaboard via USB hubs. Due to a built-in Wi-Fi chip in Pandaboard, it can support high-speed Wi-Fi based sensor nodes.

Since sensor nodes run the AES algorithm for encrypting transmitted messages, the smart gateway has to run the AES algorithm for decrypting the received messages. For being compatible with other services, the AES algorithm run in the smart gateway is implemented in Python. Decrypted messages are stored in the smart gateway's database which is built from MongoDB and JSON objects. The database combines with HTML5, XML, Django, CSS, JavaScript to provide a localhost with user interface. When a user accesses the data, the system categorizes the user as a local user or an external user via the categorization service. When a user belongs to a local network, the system directly sends the data from Fog to the user. When a user does not belong to a local network, data is sent to the user via Cloud servers. This method helps to reduce the large latency of transmitting real-time data via Cloud servers when a user belongs to a local network. The categorization service is implemented by Python and Linux packages such as "iw" and "iwconfig".

For protecting the smart gateways, Iptables and a part of our advanced security methods presented in [28,59] are implemented in the system. Particularly, the part of these methods for protecting the connection between the smart gateways and Cloud servers is merely applied. Other parts are not utilized because they can cause an increase in latency and energy consumption of sensor nodes.

In the smart gateway implementation, the QT detection algorithm, data filtering, and data processing are implemented in Python because it remains the consistency with other services. For instance, moving average filters and 50 Hz low pass filters for removing noise out of ECG signals are implemented in Python.

5.3. Cloud servers and end-user terminals

In the implementation, Google Cloud servers, API, and Cloud's services are used for storing, processing data and providing advanced services. For instance, the push notification service of the system is primarily implemented at Cloud. Similar to localhost in Fog, Cloud servers host the global web-pages which can show both real-time data and the historical data in textual and graphical forms. For accessing data, end-users can use the global web-pages or a mobile app which is built by PhoneGap for supporting both IOS and Android.

6. Experimental results

At Fog-assisted smart gateways, collected e-health data such as acceleration, angular velocity, and ECG is processed with 3 primary steps, shown in Figs. 5 and 6, including data filtering, baseline detection, and baseline wander removal. As mentioned, raw data is filtered to eliminate noise from surrounding environment. In most of the cases, the filtered data has a different baseline than the reference baseline which is 1 g, 0 deg/s, and 0 voltage for acceleration, angular velocity, and ECG, respectively. Therefore, baseline detection and baseline wander removal are applied for shifting the signals' baselines into the expected ones. Fig. 5 does not show the baseline detection step because the signals and the detected baseline overlapped in several periods. Two different methods are applied for detecting the baseline of different signals. A mean value is applied for detecting the baseline of acceleration and angular velocity while Daubechies d4 wavelet transform is applied for detecting the baseline of ECG. The processed data has the same magnitude and waveform as the filtered data and are used as inputs for algorithms such as fall detection, heart rate calculation and QT wave's length extraction shown in Section 4.1.

Parameters of the experimented room environment are 22 degrees Celsius, 31% humidity, 0.6 ppm for CO, around 8 ppb for NO_2, and 6 ppb for SO_2. These values indicate that the room environment is good. Body temperature and glucose are collected but it is not used for the comparison because its value merely slightly changes during different activities. For instance, the collected body temperature and glucose of a volunteer are around 37 degrees Celsius and around 100 mg/dl for all activities except for training (e.g., running), respectively. When a volunteer intensively runs, the core temperature increases. The blood glucose level varies depending on the monitoring time. For instance, the glucose level in the morning is lower than in the afternoon and after lunch. In our experiments, the glucose level of that person fluctuates around 90–98 mg/dl for all measurement cases.

Fig. 7 shows acceleration, angular velocity, and ECG data from the experiment. The data is collected from different activities such as standing, lying in bed, walking and running. Data in the same category is presented in the same scale for fair comparisons. Data in both cases of lying in bed and standing is stable and similar (e.g., 1 g acceleration, 0 deg/s angular velocity, and stable ECG waveform). The ECG waveform has waves such as P wave, Q, wave, R wave, S wave and T wave which are needed for algorithms (e.g., heart rate calculation and QT's length extraction). In case of lying and standing, results of the algorithms show that heart rate is 59 beats/minute, the length of QT and QTcB is around 390 and 387, respectively. In Fig. 7(a), acceleration and angular velocity slightly changes (i.e., 1.08 g acceleration and 10 deg/s angular velocity) at some moments (i.e., around 166–172th samples and 235–240th samples). These variations are expected as the user slightly moves his body two times during lying in bed. Fortunately, the ECG waveform in those moments remains stable (e.g., ECG before and during those moments is similar in terms of the number of waves, waves' magnitude, and shape of the waves such as P wave and QRS waves).

Although acceleration and angular velocity fluctuate during walking, the amplitude of the fluctuation is small when comparing to pre-defined thresholds (i.e., 2 g and 200 deg/s for acceleration and angular velocity, respectively) in the fall detection algorithm. However, the fluctuation helps to identify a walking status and calculate the number of steps of a user (e.g., by counting the number

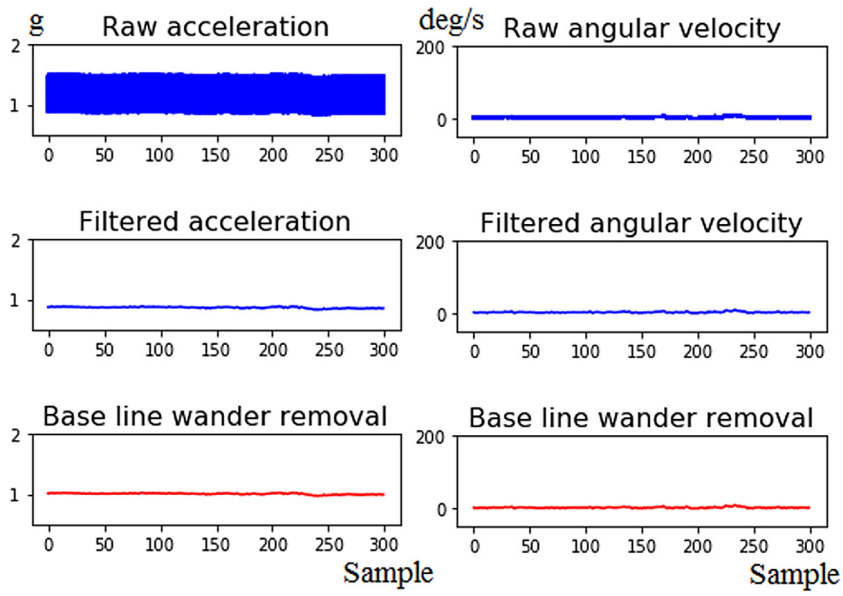

Fig. 5. Acceleration and angular velocity processing.

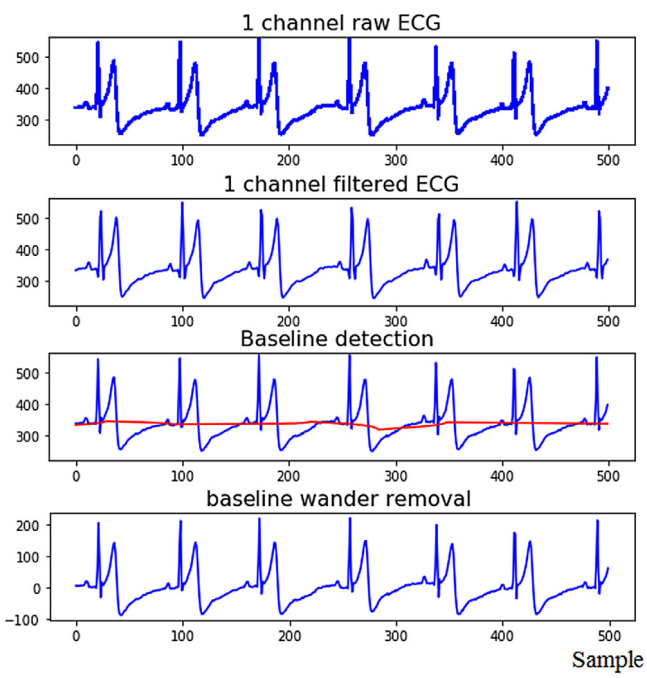

Fig. 6. ECG processing.

of top peaks of the fluctuation). Angular velocity can be used as the compliment parameter to distinguish different activities such as movement and non-movement. The shape of angular velocity waveform can be different depending on the walking or running style of the user (e.g., swinging arms and hands during walking). ECG moderately changes during walking. QRS wave, T wave, and QT's length can be detected in most of the ECG cycles whilst P wave merely appears in some of the ECG cycles (i.e., one per every 6–8 ECG cycles). In this case, QT's length and QTcB's length is around 395 and 392 ms, respectively. Comparing with ECG waves in standing and lying in bed, the ECG wave during walking is not as good as others in terms of stability.

In case of running, data fluctuates dramatically when compared with their baseline. Acceleration, in this case, shows the number of steps of a user (i.e., top peaks have much higher amplitude than the amplitude of the acceleration baseline which is 1 g). At a moment of 87–92th samples, the acceleration is higher than the predefined acceleration thresholds 2 g in the fall detection algorithm. However, the fall case is not detected by the system in this case because of two reasons. First, during 87–92th samples, angular velocity is not higher than angular velocity thresholds in the fall detection algorithm. Second, historical data shows that none of the sensors is malfunctioned. Similarly, the case of angular velocity at 58–64th samples is higher than angular velocity threshold but the fall event is not detected. ECG during walking is not as good as ECG in other statuses such as standing and lying in bed. However, P, Q, R, S and T waves appear in some of the ECG cycles (i.e., at 140–150th samples). The value of QT's length and QTcB's length varies dramatically. Therefore, it is not recommended to monitor ECG during intensive activities such as running or jumping.

In some of the experiments, a user falls in some random moments. There are 3 different falling cases during walking such as fall forward, fall back and fall aside. In this paper, fall cases during walking are focused because people are more likely to fall during activities than in static cases such as lying in bed and standing. In addition, when fall cases during activities (e.g., walking) can be detected, fall cases in other static statuses (e.g., lying in bed and standing) can be also successfully detected. Acceleration, angular velocity and ECG of these fall cases during walking are shown in Fig. 8. In most of the cases, a person tends to sit up or stand up after falling. When he sits up or stands up, the acceleration should increase to peak values. Correspondingly, two peaks including a falling peak and a standing/sitting up peak (i.e., having a higher amplitude compared to other peaks) are expected to appear in both acceleration and angular velocity waveform. In all experimented cases, these two peaks appear in the collected data. For example, two peaks of acceleration and two peaks of angular velocity appear 58–65th samples and 110–115th samples in the fall forward case. The first peak representing a fall moment often has the highest amplitude while the amplitude of the second peak varies depending on specific situations such as sitting up, standing up or crawling up. Therefore, the second peak can be smaller or larger than predefined thresholds. A distance between two peaks varies depending on different situations. In case of fall aside, at a moment after falling, angular velocity (at 125-1130th samples) does not change dramatically (i.e., reaching to a peak value) while acceleration

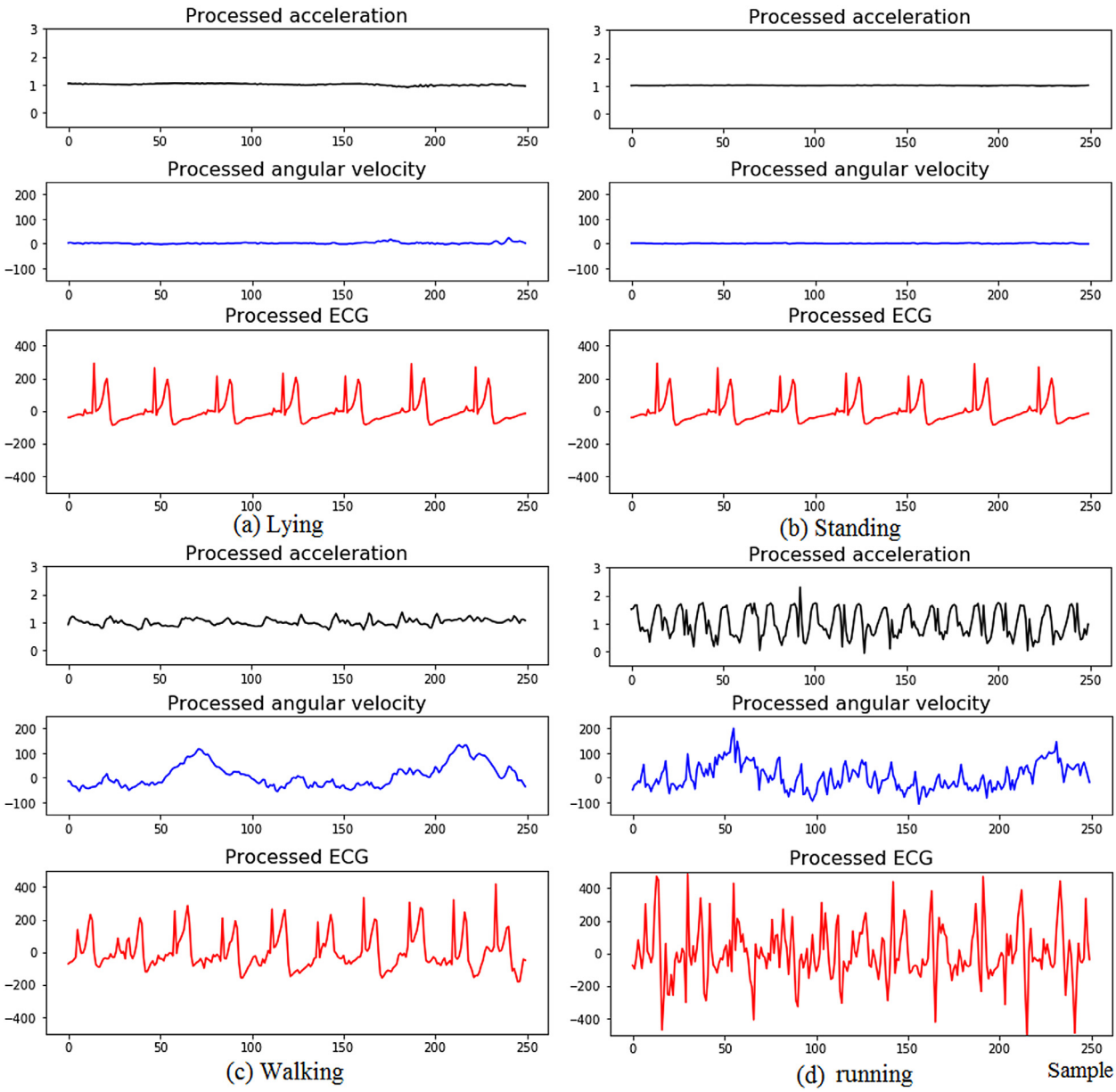

Fig. 7. Acceleration, angular velocity and ECG in different activity status.

reaches to a peak value. The reason is that a user slowly crawls and sits up after falling. It can be concluded that during fall moments, ECG fluctuates whilst ECG remains good during other moments.

In the experiments, power consumption of an e-health sensor node in different configurations is measured. In each configuration, a sensor or a group of several sensors is integrated into a sensor node. Data collected from the sensor(s) is transmitted to a gateway via nRF. Detailed information of the configurations and results of power consumption are shown in Table 2 and Fig. 9, respectively. In Table 2, the first four configurations (i.e., from Conf 1_E to Conf 4_E) are the configurations of high data rate e-health sensor nodes while the other three configurations (i.e., from Conf 5_E to Conf 7_E) are the configurations of low data rate e-health sensor nodes. The last configuration (i.e., Conf 8_E) is for the hybrid sensor nodes having low and high data rate sensors. Results show that high data rate sensors (i.e., motion sensor and ECG sensor) consume a large amount of energy while low data rate sensors consume a small amount. By using 1000 mAh Lithium battery (a size of 60 x 32 x7 mm), the low data rate sensor node (i.e., Conf 7_E) can be used up to 1639 h while the high data rate sensor node (i.e., Conf 4_E) can be used up to 173 h. In case of the hybrid sensor node, it can be used up to 157.5 h with the same battery.

Contextual sensor nodes collect and send data in every second to a gateway. Configurations and power consumption of the sensor nodes are showed in Table 3 and Fig. 10. Results show that these sensors for collecting air-related parameters (i.e., Mq2, MQ7, and MQ125) consume a large amount of power. When applying the 10 000 mAh battery having a size of 5 x 120 x 90 mm, contextual sensor nodes can operate up to 46 h. As mentioned, contextual sensor nodes are fixed in a room. Therefore, it is recommended that contextual sensor nodes should be supplied with wall-socket power. The battery is only used for a case of electricity cut.

In the experiments, sensor nodes in different configurations are applied with AES-256. Power consumption of the sensor nodes with and without is shown in Fig. 11. The results show that power consumption of the sensor nodes increases slightly (i.e., about 11% of total power of the e-health hybrid sensor node) when applying encrypting with AES-256. In this case, the hybrid sensor node can

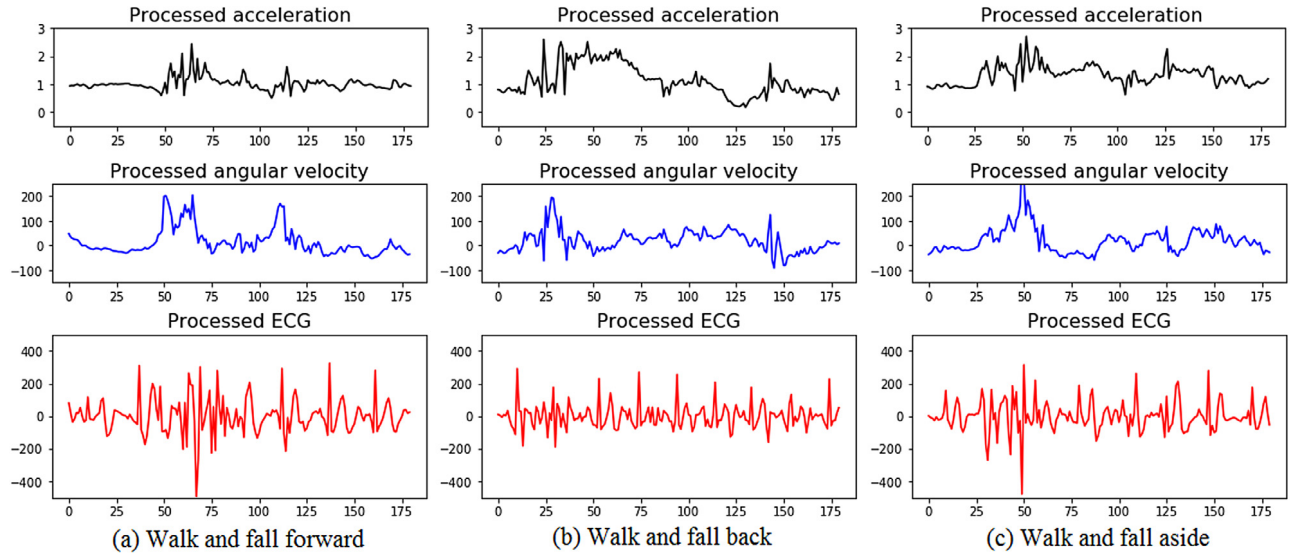

Fig. 8. Acceleration, angular velocity and ECG when a user falls in different cases.

Table 2
Configurations and average current draw of e-health sensor nodes.

Configuration	Conf 1_E	Conf 2_E	Conf 3_E	Conf 4_E	Conf 5_E	Conf 6_E	Conf 7_E	Conf 8_E
BME280					X		X	X
Samples/minute					1		1	1
Glucose sensor						X	X	X
Sample/minute(s)						1	1	1
MPU-9250			X	X				X
Sample/second(s)			50	50				50
AD8320	X	X	X	X				X
Sample/second(s)	60	120	60	120				120
Voltage (V)	3.3	3.3	3.3	3.3	3.3	3.3	3.3	3.3
Current (mA)	1.65	3.15	4.58	5.76	0.22	0.45	0.61	6.35

Table 3
Configurations and average current draw of contextual sensor nodes.

Configuration	Conf 1_C	Conf 2_C	Conf 3_C	Conf 4_C	Conf 5_C
MQ2	X				X
MQ7		X			X
MQ135			X		X
DHT22				X	X
Voltage (V)	3.3	3.3	3.3	3.3	3.3
Current (mA)	84.3	66.1	73.6	1.68	216.5

Table 4
Latency of sensor nodes and smart gateways when applying AES-256.

Device	Algorithm	Latency (μs)
Our sensor node	AES-256 encryption	1358
Smart gateway	AES-256 decryption	43
Smart gateway	AES-256 encryption	52
Cloud server	AES-256 decryption	10

operate up to 183 h. In case of contextual sensor nodes, power consumption of the nodes increases less then 0.01%. The contextual sensor nodes still operate up to 46 h when they are supplied with the 10000 mAh battery.

Results of latency for encrypting and decryption with AES-256 shown in Table 4 indicate that the latency of the sensor node increases slightly (i.e., about 1.358 ms). Correspondingly, the requirements of latency (e.g., less than 500 ms for ECG and approximately in seconds for glucose) are still fulfilled.

In this paper, power consumption of our sensor node is compared with other state-of-the-art nodes. Results shown in Table 5 indicate that our sensor node is one of the most energy-efficient sensor nodes even though our sensor node is equipped with many types of sensors for collecting motion-related data, ECG, body temperature, and glucose.

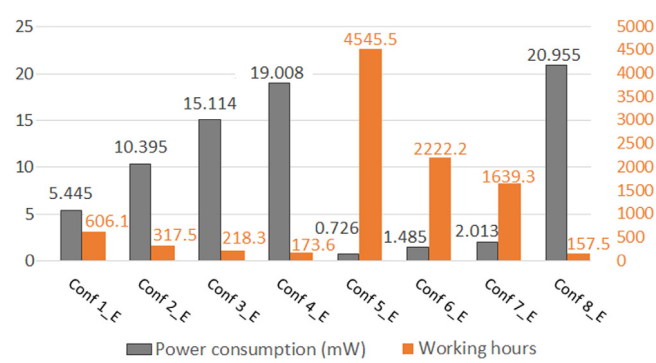

Fig. 9. Power consumption of e-health sensor node (in different configurations) with 1000 mAh battery.

Table 5
Comparisons of the proposed sensor node and other state-of-the-art sensor nodes.

Sensor node	Microcontroller (MHz)	Flash (kB)	SRAM (kB)	Sensor (s)	Voltage (V)	Power consumption
in [60]	ATmega32L (8)	256	8	Motion	5	Low
in [61]	ATmega128L (8)	128	4	Motion	3	Medium
in [62]	MSP430F2617 (8)	92	8	Motion	3.7	Low
in [63]	MSP430 (8)	48	10	Motion	3	Low
in [64]	MSP430F1611 (8)	48	10	Motion	3.7	High
in [24]	ATmega328P (8)	32	2	Motion	3	Low (36.68 mW)
in [21]	Arm Cortex M3 (24)	512	32	ECG	3.3	Ultralow
in [65]	MSP430 (8)	48	10	ECG	3.3	Low (36 mW)
in [66]	ATmega328 (8)	32	2	ECG	3.3	Low
in [67]	MSP430 (8)	48	10	ECG	3.3	Medium (64 mW)
in [30]	ATmega328P-PU (8)	32	2	Motion, ECG, body temperature	3	Ultralow (21.3 mW)
in our work	ATmega328P-PU (1)	32	2	Motion, ECG, body temperature, glucose	3.3	Ultralow (23.4 mW)

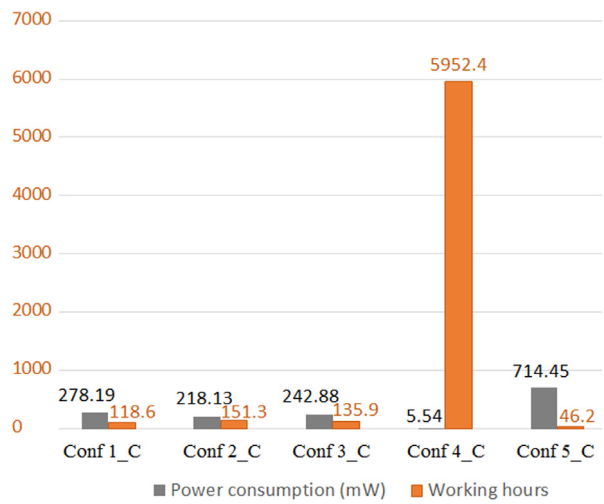

Fig. 10. Power consumption and working hours of contextual sensor nodes (in different configurations) with 10 000 mAh battery.

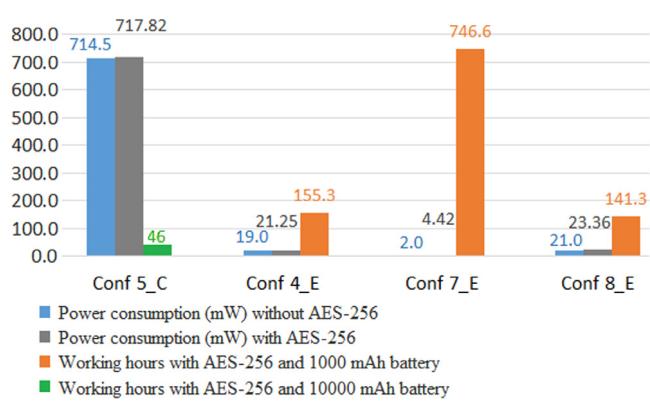

Fig. 11. Power consumption and working hours of sensor nodes in different configurations with AES-256.

7. Conclusion and future directions

In this paper, we presented a novel and smart Fog-based system for continuous, remote monitoring glucose, ECG and other signals in real-time. The complete IoT system consisting of sensor nodes, smart gateways with Fog computing and a back-end server was implemented. By simultaneous monitoring different types of signals from bio-signals (i.e., glucose, ECG, and body temperature) to contextual signals (i.e., air quality, room humidity and temperature), the accuracy of disease analysis was improved. By leveraging smart gateways and Fog computing in the system, loads of sensor nodes were alleviated whilst augmented services (e.g., local data storage, security, interoperability) were provided. In addition, we proposed algorithms for calculating the duration of QT length, fall detection, and activity status detection, respectively. These algorithms combining with the push notification service helped to improve quality of healthcare services. Results from the experiments showed that the complete sensor node for gathering glucose, ECG, motion-related signals and body temperature is one of the most energy-efficient sensor nodes and it can operate in a secured way up to 157.5 h with a 1000 mAh Lithium battery.

The future directions of this work involve diverse field. As mentioned above the sensor node battery lasts around a week. Frequent battery replacement is undesirable especially with wearable sensors as this might cause inconvenience, discomfort and even pain in case of implanted sensors.

Energy harvesting of ambient sources can be exploited for powering, recharging or extending the time between recharging of wearable micro-power sensor nodes. It involves converting the ambient energy inherent in the sensor node's environment into electrical energy. By doing so, a sensor node will have the opportunity to extend its life to a range determined by the failure of its own components rather than by its previously limited power supply. Several sources have been investigated for supplying energy to wearable sensors nodes such as solar, electromagnetic waves, indoor light, and even harvesting energy from the body of the person wearing the sensor, like piezoelectric energy from footfalls and thermal energy from temperature gradients on the skin. In previous works [31], the feasibility of RF energy harvesting has been investigated as a source for powering to the sensor. The targeted frequency band for harvesting was 925 MHz GSM band, and due to their low threshold voltage (0.2–0.3 V), Schottky diodes were utilized as rectifying element. Despite this low turn-on voltage, the rectifier will not be able to deliver any power to the load unless a voltage of 0.2 V or higher is available for forward driving the Schottky diode. For this reason, in the current work in progress, low threshold voltage diodes connected transistors are being equipped with mini solar panels attached to the transistors' gates aiding in securing the required turn-on voltage for the transistor rendering the harvesting circuit more sensitive and able to operate even at very low RF signals available at its antenna, −15 dBm [68]. While RF energy harvesting is currently able to directly power the sensor in a standard alone scenario, it can be exploited along with an efficient power management unit to recharge the battery and extend the life of the sensor node. On the other hand, the contextual sensor nodes and gateways can be completely powered autonomous when being powered by a solar along with a much simple power management unit consisting of a boost converter, a buck converter and a voltage regulator.

The use of flexible wearable and printed sensors is also being investigated, other than low fabrication cost, lightweight, better mechanical and thermal properties compared to rigid non-flexible

sensors, they are more convenient and comfortable when being used for monitoring on bendable surfaces like arms and thighs.

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References

[1] R.T. Robinson, et al., Mechanisms of abnormal cardiac repolarization during insulin-induced hypoglycemia, Diabetes 52 (6) (2003) 1469–1474.
[2] R. Vedanthan, et al., Sudden cardiac death in low-and middle-income countries, Global Heart 7 (4) (2012) 353–360.
[3] Atrial fibrillation fact sheet. Available: https://www.cdc.gov/dhdsp/data_statistics/fact_sheets/fs_atrial_fibrillation.htm [Accessed: May 2018].
[4] H.T. Nguyen, et al., Detection of nocturnal hypoglycemic episodes (natural occurrence) in children with type 1 diabetes using an optimal bayesian neural network algorithm, in: IEEE Engineering in Medicine and Biology Society 2008, IEEE, 2008, pp. 1311–1314.
[5] D. Pickham, E. Flowers, B.J. Drew, Hyperglycemia is associated with qtc prolongation and mortality in the acutely ill, J. Cardiovasc. Nurs. 29 (3) (2014) 264.
[6] L.L. Nguyen, S. Su, H.T. Nguyen, Effects of hyperglycemia on variability of rr, qt and corrected qt intervals in type 1 diabetic patients, in: IEEE Engineering in Medicine and Biology Society 2013, IEEE, 2013, pp. 1819–1822.
[7] K.D. Kochanek, et al., Deaths: Final data for 2014, Natl Vital Statist. Rep. 65 (4) (2016).
[8] WHO. Diabetes. 2017. Available: http://www.who.int/mediacentre/factsheets/fs312/en/ [Accessed: Jan 2018].
[9] Rates of new diagnosed cases of type 1 and type 2 diabetes on the rise among children, teens. Available: https://www.nih.gov/news-events/news-release/rates-new-diagnosed-cases-type-1-type-2-diabetes-rise-among-children-teens [Accessed: May 2018].
[10] C.D. Mathers, D. Loncar, Projections of global mortality and burden of disease from 2002 to 2030, PLoS Med. 3 (11) (2006) e442.
[11] D.A. Sterling, J.A. O'connor, J. Bonadies, Geriatric falls: injury severity is high and disproportionate to mechanism, J. Trauma Acute Care Surg. 50 (1) (2001) 116–119.
[12] J.A. Stevens, et al., The costs of fatal and non-fatal falls among older adults, Inj. Prev. 12 (5) (2006) 290–295.
[13] CDC. Important facts about falls. 2017. Available: https://www.cdc.gov/homeandrecreationalsafety/falls/adultfalls.html [Accessed: Jan 2018].
[14] S. Volpato, et al., Risk factors for falls in older disabled women with diabetes: the women's health and aging study, J. Gerontol. A Biol. Sci. Med. Sci. 60 (12) (2005) 1539–1545.
[15] Cardiovascular Disease & Diabetes. Dec.2017. Available: https://www.heart.org/HEARTORG/Conditions/More/Diabetes/WhyDiabetesMatters/CardiovascularDisease-DiabetesUCM313865Article.jsp/ [Accessed: Jan.2018].
[16] M.S. Kirkman, et al., Diabetes in older adults, Diabetes Care 35 (12) (2012) 2650–2664.
[17] N. Paul, T. Kohno, D.C. Klonoff, A review of the security of insulin pump infusion systems, J. Diabetes Sci. Technol. 5 (6) (2011) 1557–1562.
[18] T.N. Gia, et al., Fog computing in healthcare internet-of-things : A case study on ECG feature extraction, in: IEEE International Conference on Computer and Information Technology (CIT'15), IEEE, 2015, pp. 356–363.
[19] T.N. Gia, et al., Fog computing in body sensor networks: An energy efficient approach, in: Proc. IEEE Int. Body Sensor Netw. Conf.(BSN), 2015, pp. 1–7.
[20] Tuan Nguyen Gia, Amir M Rahmani, Tomi Westerlund, Pasi Liljeberg, Hannu Tenhunen, Fog computing approach for mobility support in internet-of-things systems, IEEE Access 6 (2018) 36064–36082.
[21] T.N. Gia, et al., Customizing 6lowpan networks towards internet-of-things based ubiquitous healthcare systems, in: NORCHIP, 2014, IEEE, 2014, pp. 1–6.
[22] T.N. Gia, et al., Fault tolerant and scalable IoT based architecture for healthcare monitoring, in: Sensors Applications Symposium (SAS), IEEE, 2015, pp. 1–6.
[23] I. Tcarenko, et al., Energy-efficient iot-enabled fall detection system with messenger-based notification, in: International Conference on Wireless Mobile Communication and Healthcare, Springer, 2016, pp. 19–26.
[24] T.N. Gia, et al., Iot-based fall detection system with energy efficient sensor nodes, in: Nordic Circuits and Systems Conference (NORCAS), 2016 IEEE, IEEE, 2016, pp. 1–6.
[25] A.M. Rahmani, et al., Smart e-health gateway: Bringing intelligence to internet-of-things based ubiquitous healthcare systems, in: Consumer Communications and Networking Conference (CCNC), 2015 12th Annual IEEE, IEEE, 2015, pp. 826–834.
[26] A.J. Jara, et al., An internet of things-based personal device for diabetes therapy management in ambient assisted living (aal), Pers. Ubiquitous Comput. 15 (4) (2011) 431–440.
[27] R.S.H. Istepanian, et al., The potential of Internet of m-health Things ḿ-IoT f́or non-invasive glucose level sensing, in: Engineering in Medicine and Biology Society, EMBC, 2011 Annual International Conference of the IEEE, IEEE, 2011, pp. 5264–5266.
[28] S.M. Moosavi, et al., Sea: a secure and efficient authentication and authorization architecture for iot-based healthcare using smart gateways, Procedia Comput. Sci. 52 (2015) 452–459.
[29] S.M. Moosavi, et al., Session resumption-based end-to-end security for healthcare internet-of-things, in: CIT 2015, IEEE, 2015, pp. 581–588.
[30] T.N. Gia, et al., Low-cost fog-assisted health-care iot system with energy-efficient sensor nodes, in: Wireless Communications and Mobile Computing Conference (IWCMC), 2017 13th International, IEEE, 2017, pp. 1765–1770.
[31] T.N. Gia, et al., IoT-based continuous glucose monitoring system: A feasibility study, Procedia Comput. Sci. 109 (2017) 327–334.
[32] A.M. Rahmani, et al., Exploiting smart e-Health gateways at the edge of healthcare internet-of-things: A fog computing approach, Future Gener. Comput. Syst. 78 (2018) 641–658.
[33] B. Negash, et al., Leveraging fog computing for healthcare iot, in: Fog Computing in the Internet of Things, Springer, 2018, pp. 145–169.
[34] H. Dubey, et al., Fog data: Enhancing telehealth big data through fog computing, in: Proceedings of the ASE BigData & SocialInformatics 2015, ACM, 2015, p. 14.
[35] Y. Cao, et al., Distributed analytics and edge intelligence: Pervasive health monitoring at the era of fog computing, in: Proceedings of the 2015 Workshop on Mobile Big Data, ACM, 2015, pp. 43–48.
[36] I. Azimi, et al., Medical warning system based on internet of things using fog computing, in: Big Data and Information Security (IWBIS), International Workshop on, IEEE, 2016, pp. 19–24.
[37] R. Craciunescu, et al., Implementation of fog computing for reliable e-health applications, in: Signals, Systems and Computers, 2015 49th Asilomar Conference on, IEEE, 2015, pp. 459–463.
[38] Y. Cao, et al., Fast: A fog computing assisted distributed analytics system to monitor fall for stroke mitigation, in: Networking, Architecture and Storage (NAS), 2015 IEEE International Conference on, IEEE, 2015, pp. 2–11.
[39] O. Fratu, et al., Fog Computing System for Monitoring Mild Dementia and COPD Patients-Romanian Case Study, IEEE, 2015, pp. 123–128.
[40] A.M. Elmisery, et al., A fog based middleware for automated compliance with oecd privacy principles in internet of healthcare things, IEEE Access 4 (2016) 8418–8441.
[41] X. Masip-Bruin, et al., Will it be cloud or will it be fog? f2c, a novel flagship computing paradigm for highly demanding services, in: Future Technologies Conference (FTC), IEEE, 2016, pp. 1129–1136.
[42] P. Davies, I. Maconochie, The relationship between body temperature, heart rate and respiratory rate in children, Emerg. Med. J. 26 (9) (2009) 641–643.
[43] M. Jiang, et al., Iot-based remote facial expression monitoring system with semg signal, in: Sensors Applications Symposium (SAS), 2016 IEEE, IEEE, 2016, pp. 1–6.
[44] V.K. Sarker, et al., Portable multipurpose bio-signal acquisition and wireless streaming device for wearables, in: Sensors Applications Symposium (SAS), 2017 IEEE, IEEE, 2017, pp. 1–6.
[45] 2.4GHz RF - Ultra low power 2.4GHz RF ICs/solutions. Available: https://www.nordicsemi.com/eng/Products/2.4GHzRF [Accessed: May 2018].
[46] Websocket. Available: https://developer.mozilla.org/en-US/docs/Web/API/WebSocket [Accessed: May 2018].
[47] Introducing to json. Available: https://www.json.org/ [Accessed: May 2018].
[48] K.W. Goh, et al., A pda-based ecg beat detector for home cardiac care, in: IEEE-EMBS 2005. 27th Annual International Conference of the Engineering in Medicine and Biology Society, 2005., IEEE, 2006, pp. 375–378.
[49] H.C. Bazett, An analysis of the time-relations of electrocardiograms, Ann. Noninvasive Electrocardiol. 2 (2) (1997) 177–194.
[50] L.S. Fridericia, Die systolendauer im elektrokardiogramm bei normalen menschen und bei herzkranken, J. Intern. Med. 53 (1) (1920) 469–486.
[51] A. Sagie, et al., An improved method for adjusting the qt interval for heart rate (the framingham heart study), Amer. J. Cardiol. 70 (7) (1992) 797–801.
[52] M. Hodges, Bazett's qt correction reviewed: evidence that a linear qt correction for heart rate is better, J. Am. Coll. Cardiol. 1 (1983) 694.
[53] P.M. Rautaharju, et al., Assessment of prolonged qt and jt intervals in ventricular conduction defects, Amer. J. Cardiol. 93 (8) (2004) 1017–1021.
[54] B. Vandenberk, et al., Which qt correction formulae to use for qt monitoring? J. Amer. Heart Assoc. 5 (6) (2016) e003264.
[55] F. Miao, et al., A wearable context-aware ecg monitoring system integrated with built-in kinematic sensors of the smartphone, Sensors 15 (5) (2015) 11465–11484.
[56] T.N. Gia, et al., Energy efficient wearable sensor node for iot-based fall detection systems, Microprocess. Microsyst. 56 (2018) 34–46.
[57] D.C. Klonoff, Cybersecurity for connected diabetes devices, J. Diabetes Sci. Technol. 9 (5) (2015) 1143–1147.

[58] N.F. Pub, Advanced encryption standard (aes), Fed. Inf. Process. Stand. Publ. 197 (441) (2001) 0311.
[59] S.M. Moosavi, et al., End-to-end security scheme for mobility enabled healthcare internet of things, Future Gener. Comput. Syst. 64 (2016) 108–124.
[60] O. Biros, et al., Implementation of wearable sensors for fall detection into smart household, in: Applied Machine Intelligence and Informatics (SAMI), 2014 IEEE 12th International Symposium on, IEEE, 2014, pp. 19–22.
[61] S.Z. Erdogan, T.T. Bilgin, A data mining approach for fall detection by using k-nearest neighbour algorithm on wireless sensor network data, IET Commun. 6 (18) (2012) 3281–3287.
[62] P. Pivato, et al., A wearable wireless sensor node for body fall detection, in: Measurements and Networking Proceedings, 2011 IEEE International Workshop on, IEEE, 2011, pp. 116–121.
[63] Y. Li, et al., Accelerometer-based fall detection sensor system for the elderly, in: Cloud Computing and Intelligent Systems (CCIS), 2012 IEEE 2nd International Conference on, Vol. 3, IEEE, 2012, pp. 1216–1220.
[64] F. Wu, et al., Development of a wearable-sensor-based fall detection system, Int. J. Telemed. Appl. 2015 (2015) 11.
[65] R. Dilmaghani, et al., Wireless sensor networks for monitoring physiological signals of multiple patients, IEEE Trans. Biomed. Circuits Syst. 5 (4) (2011) 347–356.
[66] S. Mahmud, et al., An inexpensive and ultra-low power sensor node for wireless health monitoring system, in: E-Health Networking, Application & Services, 2015 17th International Conference on, IEEE, 2015, pp. 495–500.
[67] S. Lee, W. Chung, A robust wearable u-healthcare platform in wireless sensor network, J. Commun. Netw. 16 (4) (2014) 465–474.
[68] M. Ali, et al., Autonomous patient/home health monitoring powered by energy harvesting, in: GLOBECOM 2017 - 2017 IEEE Global Communications Conference, 2017, pp. 1–7.

Tuan Nguyen Gia received his Master (Tech) from the University of Turku (Turku, Finland) in 2014. He received a 4-year funded position in University of Turku and a grant scholarship from Nokia Foundation for an efficient and excellent researcher in 2015. In addition, he receive a grant scholarship for excellent research from the Finnish Foundation for Technology Promotion. Currently, he works at the Internet-of-Things for Healthcare (IoT4Health) research group in Future Technologies department, University of Turku. His research field is Fog computing, Internet-of-Things, healthcare, FPGA, and autonomous system.

Imed Ben Dhaou (S'97-M'02, SM'2011) is an assistant professor at both Qassim University, Saudi Arabia and University of Monastir, Tunisia. He received Master's degree in Electrical Engineering from the Tampere University of Technology, Tampere, Finland, and the Ph.D. degree from the Royal Institute of Technology, Stockholm, Sweden, in 1997, and 2002, respectively. His research interests are in the areas of green data center, IoT for the smart grid, interconnect optimization, low-power circuit design, high-level power estimation, arithmetic for cryptosystems, Intelligent Transportation Systems, and VLSI for DSP and wireless systems. He has authored and co-authored more than 50 journals, book chapters, technical reports and conference papers in these areas. Dr. Ben Dhaou received the Best Paper Award from the 1997 Finnish Symposium on Signal Processing and a travel grant from the Ph.D. forum at DAC, Los Angeles in 2000. Since September 2014, Dr. Ben Dhaou has been serving as editor to the microelectronics journal, Elsevier. He was the Guest Editor for the special issue of on-chip signaling in deep-submicron technology, Journal of Analog Integrated Circuits and Signal Processing. Dr. Ben Dhaou is a vice-chair for the IEEE ComSoc, Saudi Section.

Mai Ali is currently an Instructor of Electrical Engineering at Alfaisal University, KSA. She obtained BSc degree (honors) from University of Khartoum, Sudan in 2008, and MSc in electrical engineering (with distinction) from the American University of Sharjah, UAE in 2011. Her research interests are in the areas of autonomous wireless sensor networks, energy harvesting,and low power RFIC design. She is a recipient of several awards and grants including College of Engineering research award, 2017 from Alfaisal University, Student research competition award form 41st European Microwave week, Manchester, 2011 and best student poster award from International Symposium of Mechatronics Applications, Sharjah ,2010, and 2016–2018 Internal Research Grants from Alfaisal University.

Amir M. Rahmani received his MSc from Department of ECE, University of Tehran, Iran, in 2009 and Ph.D. degree from Department of IT, University of Turku, Finland, in 2012. He also received his MBA jointly from Turku School of Economics and European Institute of Innovation \& Technology (EIT) Digital, in 2014. He is currently Marie Curie Global Fellow at University of California Irvine (USA) and TU Wien (Austria). He is also an adjunct professor (Docent) in embedded parallel and distributed computing at the University of Turku, Finland. His work spans self-aware computing, runtime resource management for systems-on-chip and resource-constrained IoT devices, wearable sensor design, and Fog Computing. He is the author of more than 150 peer-reviewed publications. He is a senior member of the IEEE.

Tomi Westerlund received his PhD (Tech) from the University of Turku (Turku, Finland) in 2008. He joined the Department of Information Technology, University of Turku as a Senior Researcher, and in 2015 became a University Research Fellow. Since 2013, he has acted yearly as a visiting scholar at Fudan University, Shanghai, China. His current research interest is Internet of Things (IoT); how we can utilize IoT technology to provide better services and improve the quality of life. With that in mind, the main application areas for his research are smart agriculture, smart cities and health technology.

Pasi Liljeberg received the MSc and PhD degrees in electronics and information technology from the University of Turku, Turku, Finland, in 1999 and 2005, respectively. He received Adjunct professorship in embedded computing architectures in 2010. Currently he is working as a professor in University of Turku in the field of Embedded Systems and Internet of Things. At the moment his research is focused on Internet of Things, Fog computing, biomedical engineering, self-aware systems, approximation computing and health technology. In that context he has established and leading the Internet-of-Things for Healthcare (IoT4Health) research group. Liljeberg is the author of more than 270 peer-reviewed publications.

Hannu Tenhunen received the diplomas from the Helsinki University of Technology, Finland, 1982, and the PhD degree from Cornell University, Ithaca, NY, 1986. In 1985, he joined the Signal Processing Laboratory, Tampere University of Technology, Finland, as an associate professor and later served as a professor and department director. Since 1992, he has been a professor at the Royal Institute of Technology (KTH), Sweden, where he also served as a dean. He has more than 600 reviewed publications and 16 patents internationality. He is a member of the IEEE.