IEEE Access
SPECIAL SECTION ON DEEP LEARNING ALGORITHMS FOR INTERNET OF MEDICAL THINGS

Received March 24, 2020, accepted April 11, 2020, date of publication April 15, 2020, date of current version May 4, 2020.

*Digital Object Identifier 10.1109/ACCESS.2020.2988059*

# IoT-Assisted ECG Monitoring Framework With Secure Data Transmission for Health Care Applications

**GUANGYU XU**
School of Computer Information Management, Inner Mongolia University of Finance and Economics, Hohhot 010070, China
e-mail: nmgxgy@imufe.edu.cn

This work was supported by the Project of the National Natural Science Foundation of China (Research on the Evolution Mechanism of Power System Disaster Risk in Inner Mongolia from the Perspective of Disaster Chain) under Project 71961022.

**ABSTRACT** The emerging Internet of Things(IoT) framework allows us to design small devices that are capable of sensing, processing and communicating, allowing sensors, embedding devices and other ' things ' to be created which will help to understand the surroundings. In this paper, the IoT assisted electrocardiogram (ECG) monitoring framework with secure data transmission has been proposed for continuous cardiovascular health monitoring. The development and implementation of a lightweight ECG Signal Strength Analysis has been proposed for automatic classification and realtime implementation, using ECG sensors, Arduino, Android phones, Bluetooth and cloud servers with the proposed IoT-assisted ECG monitoring system. For secure data transmission, the Lightweight Secure IoT (LS-IoT) and Lightweight Access Control (LAC) has been proposed. The ECG signals taken from the MIT-BIH and Physio Net Challenges databases and ECG signals for various physical activities are analyzed and checked in real-time. The proposed IoT assisted ECG monitoring framework has great potential to determine the clinical acceptance of ECG signals to improve the efficiency, accuracy and reliability of an unsupervised diagnostic system.

**INDEX TERMS** Internet of Things (IoT), ECG monitoring system, lightweight secure IoT (LS-IoT), lightweight access control (LAC).

## I. INTRODUCTION

Medical care services have been one of the most significant problems for both people and governments with a rapid increase in human populations and preserve usage [1]. Whereas, the problems of the maturing population are more real, according to a study from the World Health Organization (WHO) [2]. The health status of elderly people must be checked more often, a more prominent test of current medicinal frameworks [3]. Careful consideration must be given to identifying human diseases in a comfortable and precise way at a low cost. Because of the growth, experience and expertise gained over the years in cardiac analysis [4], the diagnostics focused on the electric cardiogram (ECG) in both treatments and medical research have become widely related. The ECG is widely recognized in professional medical foundations by enormous and stationary devices [5], [6].

The associate editor coordinating the review of this manuscript and approving it for publication was Wei Wei.

The equipment usually uses twelve electrodes to collect ECG information in one centralized location, because the system is possibly not flexible, which means that activities for the patients are highly limited during information collection [7]–[9]. However, as these devices are usually excessively expensive for home usage, patients have to always attend a doctor's office that ultimately raises the weight of the medical facilities. There is a strong desire for a flexible long-distance ECG signal recognition system with low costs [10].

Figure 1 shows the Structure of the IoT assisted ECG monitoring framework. IoT-driven health and wellness systems allow remote and continuous monitoring of people with chronic conditions such as obesity, high blood pressure, diabetes, hyperglycemia, asthma, depression, help for elderly, preventative care and well-being [11]–[13]. Improving the affordability and quality of care and significantly reducing the treatment costs and daily trips will play a major role in improving IoT health and wellbeing [14]. The IoT-based healthcare system uses connected bio-sensors

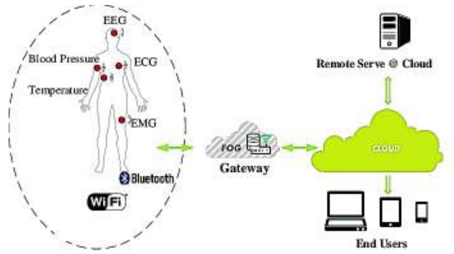



**FIGURE 1.** **Structure of IoT assisted ECG monitoring framework.**

that collect numerous biomedical signals and connectivity to share/communicate the signals received instantly to the internet and health care providers [15]. Furthermore, remote monitoring applications enabled with IoT can significantly reduce long-term monitoring applications in terms of travel, costs and time [16].

IoT has become one of the most effective information collection and communication concepts in health and fitness monitoring environments including highly personalized health services, environmentally assisted living, user attitude identification, and behavior recognition [17], [18]. The author developed Wireless Sensor Networks for the Evaluation of Joint Angles and vital signals to assist physiotherapists in real-time with the IoT-based physiotherapy network. For wireless health surveillance systems, longevity communication is an important challenge for WBAN's energy-constrained availability of small sensor nodes with energy [19]–[21].

The main contribution of this paper to provide a new cardiovascular IoT signal strength analysis for the wearable networks of the medical body areas. To implement a methodology for a reliable lightweight signal quality assessment to increase battery life for IoT-enabled wearable devices and to reduce traffic, bandwidth and cloud-based processing costs. The Lightweight Secure IoT (LS-IoT) and Lightweight Access Control (LAC) has been proposed for improving the data transmission security.

## II. RELATED WORKS

IoT has a vital role to play in the creation of health-care facilities for the increasing rural population. As a diagnostic tool for cardiac problems, the ECG monitoring system plays a major role. This makes the implementation of a Portable Point of Care (POC) system [22] at an affordable cost critical in order to monitor the cardiovascular health of the patients without competing with their daily routine. They had developed a workflow of three important modules to complete the end of health services. Next, a portable ECG monitor system with a limited shape factor is activated with Bluetooth Low Energy (BLE). Next, an Android app that receives, records, and analyzes data sent from the ECG device on a smartphone. Lastly, a virtual repository where patient data and analytical reports are preserved for a medical practitioner's reference. The device was validated using real-time data collected from a local hospital and ECG signals were compared to GE and SIEMENS ECG standard systems.

Zhang *et al.* [23] introduced a Portable Short Range Wireless Technology (PSRWT), WIFI enabled seven-lead electrocardiogram (ECG) monitoring system. The 7-lead ECG monitoring package is mainly composed of ECG preprocessing, the built-in analog front end, the microcontroller, a Wi-Fi wireless network and the power modular device. The system mainly comprised of two parts: a 7-lead ECG control unit and an ECG monitoring framework. Miniaturization, low power, and high performance are the advantages of this approach. The ECG wireless transmission system uses Wi-Fi for transmitting ECG data into the ECG waveform monitoring center, controlled by a seven-lead ECG monitoring unit. Physician who earns medical status from the ECG home surveillance system or elderly individuals who may alert older individuals of suspicious ECG signals in time for a further physical exam to reduce the rate of cardiovascular mortality suddenly.

The author has introduced QRS detection in real-time of the ECG signal on the IOS smartphone to determine cardiac arrhythmia in patients who are ambulatory through the remote patient surveillance system [24]. Data will be collected on a single channel, by a functional ECG system that is connected to and transmitted on a smartphone as monitored and processed. The QRS detection of obtained ECG signal is carried out in the mobile application developed using the target C programming language and performed in different steps using the Pan-Tomkins (PT) process.

Liu *et al.* [25] developed a new wearable 12-lead, IoT-based ECG SmartVest Cardiovascular Disease Early Detection Device consisting of four usually IoT-based components: 1) fabric sensor layer using the electrical dry ECG electrode; 2) Bluetooth network layer, Wi-Fi and so on; 3) cloud storage and measurement system and server; 4) Signal processing and device decision-making layer. The focus of our work is on the challenges presented by SQA and QRS for wearable ECG applications. First, a hybrid system of multiple signal reliability indices and machine learning is proposed for the classification of 10-s of single-channel ECG segments as acceptable and unacceptable. Thus an accurately located QRS complex is built with a lightweight QRS detector. This paper shows that the ECG SmartVest device developed for IoT-driven applications and has a promising application to be used to track the population widely in everyday life.

Wannenburg *et al.* [26] developed and implemented the idea of a portable wearable device able to calculate electrocardiogram (ECG) and respiration rate (RR) by using capacitive electrodes. ECG, as well as RR, had been calculated with an active electrode and an analog conditioning circuit only. Bluetooth uses low energy to connect wirelessly to the remote server. The calculated data are used to determine the variation in heart rate, RR, and ECG-related characteristics. The use of

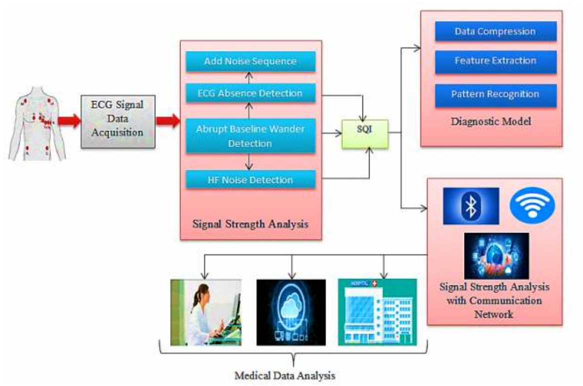



**FIGURE 2.** Proposed Signal Strength Analysis (SSA) Framework based on IoT platform.

non-contact active chest electrodes has been found to be a feasible measuring method.

Based on the above survey, there are some issues in ECG Signal Strength Analysis. In this paper, the IoT assisted ECG monitoring framework with secure data transmission has been proposed for continuous cardiovascular health monitoring. The development and implementation of a lightweight ECG Signal Strength Analysis has been proposed for the automatic classification and realtime implementation with an IoT-assisted ECG monitoring system.

## III. MATHEMATICAL MODEL FOR IOT ASSISTED ECG MONITORING FRAMEWORK

Figure 2 demonstrates the principle modules of the signal strength analysis (SSA)-IoT platform. It consists of three modules: (1) ECG module for the sensing of signals, (2) the automated module for the assessment of signals quality and (3) an ECG analysis and a transmitter module for the quality of the signal. This paper concentrates on the design and implementation in real-time of an automated ECG signal quality assessment process and assesses the feasibility of the proposed SSA-IoT system under the rest, patient and physical activity conditions.

In order to estimate the clinical acceptability of ECG signals, the proposed (ECG-SSA) automated signal strength analysis approach is a three-phase process. This includes flatline (or the total absence of the ECG signal), abrupt extraction and high-frequency noise detection and extraction from the baseline. The ECG-SSA is applied through the discrete filter, turning points and decision-making rules based on the transformation of the Fourier (DFT).

3.1 Baseline Removal and Detection of Abrupt Change.

ECG signals are primarily affected by physical activity, body motion, skin-electrode interfaces, variable impedance between electrodes and the skin due to the lack of contact with electrons and abruptness throughout the operation. The basic changes may decrease the quality of the ECG signal during physical activity and can affect PQRST systems adversely. By involving the baseline wanders in abrupt changes, the local wave characteristics of the ECG beats are more difficult to determine. The baseline wandering frequency is lower than 0.8 Hz (up to 1 Hz when stressed).

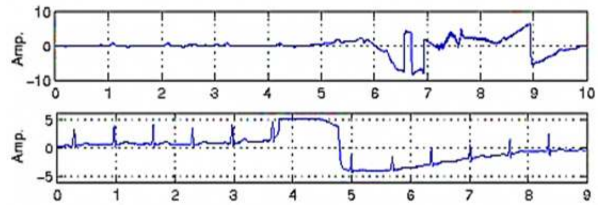



**FIGURE 3.** It illustrates the abrupt baseline wandering detection. (a) ECG signal is corrupted by abrupt baseline wanders in the MIT-BIH database. (b) The baseline *yp*) wander signal from equation (2).

This uses the discrete filter approach based on Fourier Transformation (DFT) for the detection of basic errors. Let $[p], p = 0, 1, 2, \ldots q - 1$ be an ECG signal of discrete-time. The $a[p]$ has been calculated as baseline wander detection.

$$A[h] = \sum_{p=0}^{P-1} a[p] e^{\frac{-ip\pi h}{P}} \tag{1}$$

$A[h]$ denotes h$^{th}$ DFT Coefficient. DFT coefficients of less than 1 Hz have been taken from the baseline. DFT coefficient indices $h$ for the component of the FHz are determined as

$$h = \frac{FP}{Fx}.y[p] = a[p] - \hat{a}[p] \tag{2}$$

When the baseline wandering signal is $y[p]$ and $\hat{a}[p]$ is the baseline wandering removed signal calculated as

$$\hat{a}[p] = \frac{1}{P} \sum_{p=0}^{P-1} \hat{A}(h) e^{\frac{ip\pi h}{P}} \tag{3}$$

$\hat{A}$ denotes a vector with the DFT threshold coefficient that is achieved as $\hat{A}(h) = [0, \ldots\ldots 0, A[h+1], \ldots A[P-h-1]]$. Figure 3 displays an ECG signal derived from the baseline wander signal. Results show that the baselines wander exhibits high variation in amplitude over a short period. This further analyses the derived signal, to distinguish the abrupt baseline drift from starting to change baseline wanders.

$$X_c = max\{|y[p]|\} \tag{4}$$

where $X_c$ is the amplitude dynamic value. When $X_c$ reaches a predefined threshold, either baseline or abrupt baseline drift is either observed. In some cases, a basic component can be removed without distortions of ECG signal information, but the removal of an abrupt baseline drift is difficult, without distorting the ECG signal components, which further analyzes an abrupt baseline drift signal.

The baseline wander $y(p)$ signal is divided first into blocks of 500 ms in block size (C), and 50% overlap (D) in block.

$$\hat{y_h}(p) = y\left(\frac{Ch}{2} + p\right) \quad p = 1, 2 \ldots .T \tag{5}$$

where $\hat{y_h}(p)$ is a h$^{th}$ block of $y(p)$ and $T$, the number of blocks is the $y_h(p)$ block. Let $\hat{x_h}$ be a local dynamic range of $y_h(p)$.

$$z_j = \hat{x}_{j+1} - \hat{x}_j, \quad j = 1, 2, \ldots .T - 1 \tag{6}$$

After that, the approximate $z_j$ of the correct baseline drift case is contrasted with the predefined threshold.

$$SQI_{ABD} = \begin{cases} 1, & max\{|z|\} > \beta \\ 0, & otherwise \end{cases} \tag{7}$$

When the $SQI_{ABD}$ is related to the Signal Quality Index (SQI), for the abrupt baseline drift event (ABD). The $\beta$ is here selected as 0.2 mV to detect the abrupt baseline wanders capable of changing the ST segment and the other low-frequency ECG signal elements. The ECG signal is considered inappropriate in case of abrupt baseline wandering occurrences. The ECG signal is a good signal since it can be extracted from a sample without distorting the PQRST complex considerably.

### A. ABSENCE DETECTION OF ECG SIGNAL

The sensor shows the lack of ECG signal information in the signal obtaining, as the skin and the electronic saturation components are disconnected from the electrodes. The graph shows, in fact, the presence of the flat line of zero amplitude (ZFL), only wandering baseline, and exterior and physiological noise. For the detection of the ZFL event, existing approaches have been developed. It presents a new approach for the detection of the above-mentioned noise events in this work.

The flat line detection is described as follows,

Add very small equally distributed random noise to the $a[p]$

$$k[p] = \hat{a}[p] + xr(p) \tag{8}$$

For a certain number of turning points, random noise is applied to the signal. The amplitude of the A scale is 0.01 mV. If there is no ECG, the distorted signal $k[p]$ has several turning points.

Calculate the number of turning points (tp) with a criterion for a noisy signal $k[p]$.

For a noisy signal $k[p]$, calculate the number of turning points (tp) with the threshold.

$$SQI_{FT} = \begin{cases} 1, & tp > 0.66M \\ o, & othewise \end{cases} \tag{9}$$

If $SQI_{FT} = 1$, then the segment is labeled as a flat line or an absence of the ECG signal. The section is otherwise further analyzed for the identification of high-frequency noises.

If $SQI_{FT} = 1$, then the segment is defined as an ECG signal or a flat line. The portion is otherwise evaluated for high-frequency noise detection.

In fact, the abnormal health of the people could be seen in real-time ECG records as a result of a sudden, long-term breakup. Therefore, the Signal Quality Index is stored and forwarded to the diagnostic server for each processed ECG segment. In comparison, when the absence of an ECG signal, as is the case for traditional ECG monitoring systems, the subject is immediately changed.

### B. DETECTION OF HF NOISE

High-frequency noises (HF), such as muscle artifacts, power line interference, motion artifacts, delay, and noise, are used to provide the ECG signal. The local waves (P, T, U, and the low amplitude QRS) of the ECG signal may be distorted by the HF noises. It is therefore difficult to accurately and confidently calculate the frequency, duration, pause distance, time, polarity and shapes of the local waves. Especially removing HF noises, muscle noise, without distorting the local signal waves, is very complicated. This paper provides, therefore, a basic HF Noise recognition based on the turning points and threshold rule:

- ❖ Use maximum amplitude to normalize the ECG signal.
- ❖ Segment the normalized signal $\hat{a}[p]$, into blocks of the block size (S) of 2 s which are not overlapped.

$$\hat{a}_h(p) = \hat{a}(Sh + p) \quad p = 1, 2, \ldots..S \tag{10}$$

where $h = 0, 1 \ldots Q_1 - 1$ and $Q_1 = \frac{Q}{S}$

- ❖ A $\mu H$ amplitude threshold of 0.05 mV for calculation of turning points on the basis of an appropriate HF noise level, that does not distort small amplitude waves on the local ECG signal. Calculate the number of turning points and the position of each $\hat{a}_h(p)$.
- ❖ Check the minimum two turning points distance

$$r_h = min\{tp(j+1) - tp(j)\}, \; for \; j = 1, 2, \ldots..T1 \tag{11}$$

where $T1$ is the h$^{th}$ block $tp$ frequency.

- ❖ Implement decision rules for HF noise detection of the ECG segment

$$SQI_{HF} = \begin{cases} 1, & G_1 \| G_2 \\ o, & othewise \end{cases} \tag{12}$$

When R1 is more than 5% of the sample number in a certain block (tpk), then $G_2$ is more than 5%, and $G_2$ is valid if the difference between the two turning points $r_h$ is less than two.

If $SQI_{HF} = 1$ the segment is classified as a higher frequency noise segment, then the segment is classified as a high-frequency noise-free ECG.

### C. QUALITY GRADING OF THE ECG SIGNAL (QGS)

The ECG signal is measured in this Section based on the decisions taken on the abrupt baseline wandering, absence of ECG signals and high-frequency sounds, with the ECG signal classification in 3 groups, such as good medium and bad based on the HF noise ratings. The existence of flat and abrupt simple wanderings can contribute to noisy clinical features. On the basis of the results of the assessment, it has been observed that the ECG signal with some HF noises can calculate some morphological characteristics and RR intervals. So the noisy ECG signal is graded as medium and bad. Finally, the quality of the signal is measured as

$$QGS = \begin{cases} Good, & SQI = 0 \\ Medium, & SQI = 0.5 \\ Bad, & SQI => 0.5 \end{cases} \tag{13}$$

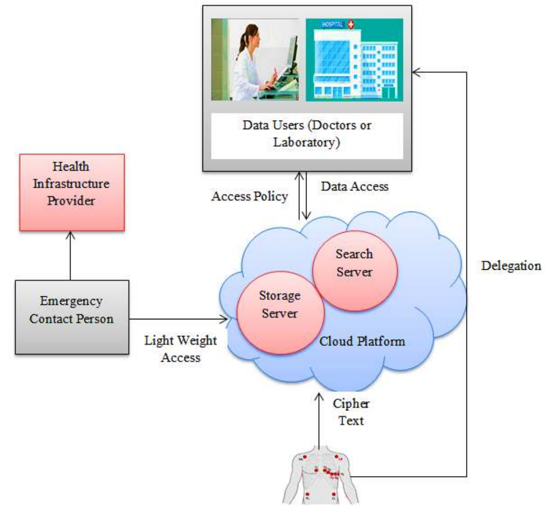



**FIGURE 4.** **Lightweight access control for secure ECG data transmission.**

Then SQI is measured as

$$SQI = SQI_{ABD} + SQI_{FT} + SQI_{HF} \tag{14}$$

The good quality of the ECG signal indicates that noise levels are appropriate, the morphological characteristics do not distort, while the moderate and low quality of noise levels are shown in moderate and bad indications. This assumes the medium class of ECG signals can be used for an ECG-specific signal processing systems.

### D. MATHEMATICAL MODEL FOR SECURE ECG DATA TRANSMISSION LIGHTWEIGHT ACCESS CONTROL (LAC)

The architecture of the LAC includes the main core for generation of data, a cloud platform (PT), data owners, the patient, data users and an emergency contact person which is shown in figure 4.

The device should be indistinguishable from the attack of plaintext to ensure the security of the Attribute-based access (ABE) encrypted medical files. The basic safety model that an adversary cannot discern in the two underlying complaints two ciphertexts of threat. The security of the attack has fully security model. In the security model, the adversary designates the access policy for challenges at this challenging stage rather than at the very start. It is evident that the full security model has a greater level of protection than the other selective model.

### E. SECURITY ANALYSIS

Assume that Diffie- Hellman (DH) is a decisional bilinear assumption, therefore LAC is fully secure.

*Proof:* Suppose an opponent $X$ is able to distinguish various ciphertexts. After that, it creates an algorithm $Z$ that breaks the DH assumption that DH increases. $\vec{b} = (h_1, h_1^x, h_1^y, h_1^z)$

*Configuration:* The competitor $Z$ chooses $\delta', \varepsilon \in TC_q^*$ and implicitly set $\delta = \delta' + xy$. Compute $B = e\left(h_1^x, h_1^y\right) e\left(h_1, h_1\right)^{\delta'} = e(h_1, h_1)^{\delta}$ *and* $h_1 = h_1^{\varepsilon}$ sends a public key $PB = (h_1, h_2, B)$ to $X$.

*Case 1:* The following queries are adapted to X.

(1) $\boldsymbol{Q_{sk}}$ : $X$ Queries for the Secret S attribute key. $Z$ selects $k_1, k_2, \rho, p' \in TC_q^*$ and sets to $p = xy + p'yZ$ selects $l_j \in TC_q^*$ and that the $l_j$ inverse in $C_q^*$ for $j \in [l]$. Set $\vartheta_j = y.l_j^{-1} - \varepsilon$ and create $sk_3 = l_1, sk_4 = l_2, sk_5 = \rho$

$$\begin{aligned} sk_1 &= h_1^{\delta - p} = h_1^{(\delta' + xy) - (xy + p'y)} \\ &= h_1^{(\delta' - p'y)} = h_1^{\delta'}.(h_1^y)^{p'} \\ sk_{2,j} &= h_1^{p(\delta_j + \varepsilon)^{-1}} = h_1^{(\delta' y + xy)(y.l_j^{-1} - \varepsilon + \varepsilon)^{-1}} \\ &= h_1^{(\delta' y + xy)(y^{-1} l_j)} = h_1^{l_j(x + p')} \\ &= (h_1^x)^{l_j}.h_1^{l_j p'} \end{aligned}$$

Secret Key SK $= \{sk_1, sk_{2,j}, sk_3, sk_4, sk_5\}$ is send to $X$

(2) $\boldsymbol{Q_{dk}}$ : $X$ query on the application device delegation key with set $S.Z$ attributes are running $Q_{sk}$ to construct the secret $SK$ attribute and computes $dk_1 = sk_1^{sk_5}, dk_{2,j} = sk_{2,j}^{sk_5}, dk_3 = h_1^{sk_3}, dk_4 = h_2^{sk_4}$. The created delegation key is $DK = \left(dk_1, \left\{dk_{2,j}\right\}_{j \in [h]}, dk_3, dk_4\right.$ which is send to $X$.

(3) $\boldsymbol{Q_{pd}}$ : $X$ Ciphertext $CT$ partial decryption query issue is running on $Q_{dk}$ in order to build $DK$ for data users with the attribute set $S.Z$. $Z$ calculates

$$\begin{aligned} \tau = e\left(Z_1, dk_1\right) e(dk_3, \textstyle\prod_{j \epsilon J} dk_2^{Z_{2}, j.\sigma_i}) \\ \times e(dk_4, \textstyle\prod_{j \epsilon J} dk_2^{Z_3, j.\sigma_i}). \end{aligned}$$

Then $CT' = C_N, C_0, \tau$ send to $X$.

(4) $\mathbf{Q_{de1}}$ : Problems of ciphertext $CT$ type-1 decryption for data users with attribute set $S$. $S.Z$ runs $Q_{pd}$ to build the transformed $CT'$ and $Q_{sk}$ to build a secret SK attribute. $Z$ calculates $\gamma = C_0, \tau$ *and* $Sde(K_3\left(\gamma\right), C_N)$ to transfer message $N$.

(5) *Problem:* $X$ sends a policy of access $(X^*, \sigma^*)$ a message $N^*$ and two challenge data $(\gamma_0^*, \gamma_1^*)$ to $Z$, where $X^* \in C_q^{k^* \times m^*}$ and $\sigma^*$ compares $X^*s$ rows to attributes. The requirement is that in case 1 there is no issue of a secret tribute key of the set S which satisfies $(X^*, \sigma^*)$ attribute.

*Case 2:* It is like case 1, where $S$ does not satisfy the constraint

*Assumption:* $X$ outputs assume $\vartheta' \epsilon \{0, 1\}$. If $\vartheta' = \vartheta$, $Z$ outputs 1 indicates $K = e(h_1, h_2)^{x,y,z}$ otherwise, it outputs 0 where $K$ is random.

### F. LIGHTWEIGHT SECURE IoT (LS-IoT)

The LSHS consists of five components: the key generating center (KGC), patients, edge servers (ES). It includes the cloud server and doctors, as shown in Figure 5. In the lightweight, secure health care data transmission system, each part plays the following role:

- The KGC initializes the system and generates secret keys that support their identity for patients and edge servers.

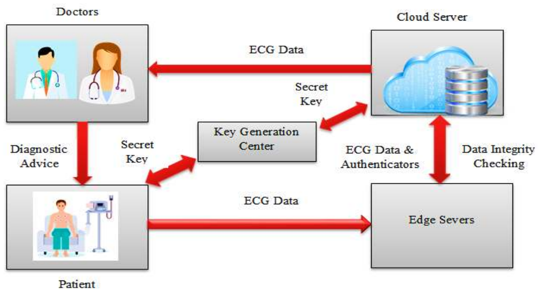



**FIGURE 5.** LS-IoT based secure data transmission.

- The proposed lightweight secure health storage system connects every patient to certain sensors. Such sensors capture patients ECG data. Such ECG data is stored for patient care on a cloud server. The sensors encrypt ECG data directly and send it to the next-end edge server for processing to relieve its own pressure.
- The patient edge server is to measure the authentication of patient health information and upload the authentication and data to the cloud server. Patients can send public data to any edge server to check the validity of ECG data that they store on their cloud server.
- The CS stores the encrypted ECG Data for the patient. If the doctor asks for access to the ECG data of a patient, CS authenticates the identity of the doctor and gives the decrypted ECG data to the doctor.
- Doctors analyze patient ECG data stored on the cloud server and provide patients with appropriate advice.

### G. SECURITY ANALYSIS INTEGRITY OF DATA

*Case 1:* In the LS-IoT the probability of $Q_d$ of health data detection divided in $Q_c \geq 1 - \left(\frac{M-m}{M}\right)^f$, in which $M$ is time slices per day, $m$ is $m$ time slices, in which health data is broken in the cloud server and the time slices in Chal are challenged.

*Proof:* Assume that $Q_0$ do not detect broken health data, then it has:

$$\begin{aligned} Q_d &= 1 - Q_0 \\ &= 1 - \frac{M-m}{M} \cdot \frac{M-m-1}{M-1} \cdot \ldots \cdot \frac{M-m-f+1}{M-f+1} \\ &\geq 1 - \left(\frac{M-m}{M}\right)^f \end{aligned}$$

The proposed system for checking data integrity, therefore, allows the completeness of health data stored on the cloud server to be checked effectively. The lowest likelihood of detection of Fix N at 10000 is shown in figure 6, which varies with n and c. The lowest probability of detection has been shown to be almost 1 if $m$ is 80 and $f$ is 500.

### H. CONFIDENTIALITY AND AVAILABILITY OF DATA

Patient P and cloud servers perform the protocol of key exchange and receive secret key SK. P encrypts $n'_{ji}$ *as* $n_{ji} = E_{SK}$ and sends ciphertext $n'_{ji}$ as ES before sending health data into the Edge server ES. ES is unable to obtain $n'_{ji}$ without secret key SK. Therefore the data on health can be secured. By decrypting $n_{ji}$ as $n'_{ji} = E_{SK}(n_{ji})$, a cloud server can use the secret key SK. The quality of data is therefore not affected.

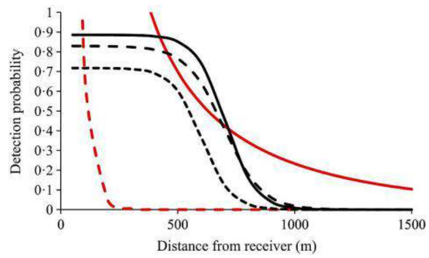
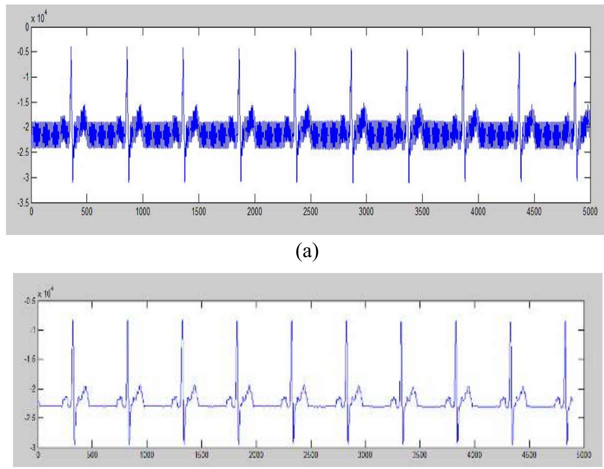



**FIGURE 6.** Detection probability.



(a)

(b)

**FIGURE 7.** (a) ECG signal with low-frequency and high-frequency noises corrupted, 7(b) bad quality ECG signal obtained under extensive activity.

### I. SECURITY AND AUTHENTICITY OF IDENTITIES

The patient $P$ gets a pseudonym $PSp$, which is used for sending health information to the ES edge server. This method prevents patient's identity information from being exposed to the ES edge server and maintaining the integrity of the patient's identity. The quality and performance of the proposed method has been analyzed based on the results and discussion section.

## IV. RESULTS AND DISCUSSION

### A. IMPACT ON THE QUALITY OF ECG THROUGH PHYSICAL ACTIVITY

ECG signals are monitored for longer periods of time to examine the effect of physical activity on the ECG signal strength. The ECG Signals are recorded in four activities: sitting, walking, meditation and body movements. Figure 7 shows the bad ECG signal received during active practice from the subject. The ECG signal obtained has shown that it is more accurate and reliable to extract clinical properties (Figure 7(a)). In Figure 7 (b), the acquired ECG signal reveals the abrupt baseline and activity delay.

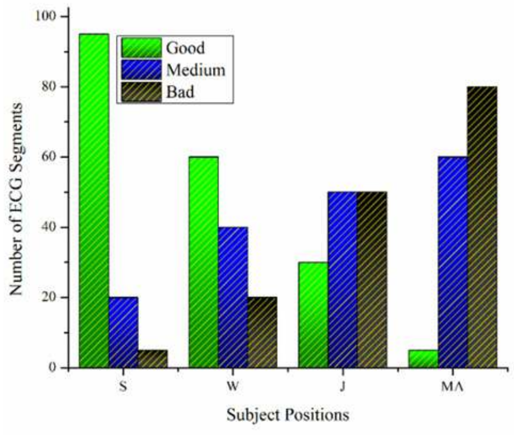



**FIGURE 8.** Quality evaluation of the ECG signals obtained during the different physical activities.

Figure 8 shows the ECG segments recorded in the above-mentioned physical activity. The proposed system tests the consistency of the ECG signal in three degrees: good, medium and bad. The test study shows that in sitting and normal walking scenarios the consistency of the acquired EECG signals is good. The results from previous experiments show furthermore that the ECG signals obtained during jogging and other large activities are severely damaged by high-frequency noise and artifacts. It plays a major role in the understanding of the ECG context. Moreover, processing and transmission power can be significantly reduced if the ECG signals are obtained in high-intensity scenarios where Sitting-S, Jogging-J, Walking-W, Muscle Activity- MA.

### B. THE EFFICIENCY OF THE SSA METHOD

Table 1 summarizes the overall evaluation results for the MITABIHA and Physionet Challenge segments as well as real-time ECG signals obtained by 20 subjects. The results show that, for noise-free and noisy ECG signals obtained from datasets, an average sensitivity of over 98% and 99% is available from this proposed SSA method. SSA achieved an average sensitivity of more than 99% and 93% respectively with the noise-free and noisy ECG signals in Physionet Challenge databases. The SSA process results in an average sensitivity of around 90%, or 96% respectively between the noise-free and noisy ECGs during physical activities. Three SSA approaches are used in performance comparisons based on the QRS detecting characteristics and design communication, QRS detection and RR- interval features and heuristic regulations, as well as statistical characteristics.

The efficiency of four SSA methods is described in Table 2. Results show that the proposed SSA methodology exceeds other approaches focused on morphological, RR, and machine learning. The Automatic SSA is simple and suitable for the evaluation of the consistency of the ECG signals generated in the real-time environment as compared to the signal processing techniques of the existing methods.

**TABLE 1.** The efficiency of the SSA method.

| Datasets | Signal Type (ECG) | Segments | True Positive | False Negative | Sensitivity (%) |
|---|---|---|---|---|---|
| MITBIHA | Noise-Free | 500 | 495 | 5 | 99.42 |
| | Noisy | 998 | 992 | 6 | 99.78 |
| Physionet | Noise-Free | 411 | 409 | 2 | 99.85 |
| | Noisy | 298 | 281 | 17 | 93.2 |
| | FL | 80 | 80 | 0 | 100 |
| Real time Data | Noise-Free | 1300 | 1210 | 90 | 90.23 |
| | Noisy | 500 | 476 | 24 | 96.54 |

**TABLE 2.** Efficiency comparison of SSA methods.

| SSA Method | Signal Type (ECG) | Segments | True Positive | False Negative | Sensitivity (%) |
|---|---|---|---|---|---|
| PSRWT | Noise-Free | 2200 | 1702 | 498 | 79.5 |
| | Noisy | 1800 | 1400 | 400 | 70.9 |
| PT method | Noise-Free | 2200 | 1657 | 543 | 80.7 |
| | Noisy | 1800 | 1396 | 404 | 75.6 |
| SmartVest | Noise-Free | 2200 | 1956 | 244 | 83.7 |
| | Noisy | 1800 | 1562 | 238 | 89.8 |
| Proposed IoT-assisted ECG monitoring system | Noise-Free | 2200 | 2112 | 88 | 96.5 |
| | Noisy | 1800 | 1756 | 44 | 98.4 |

### C. POWER CONSUMPTION

The proposed algorithms on Android Phones are used to illustrate the energy efficiency benefits in order to acquire, process and transmit a suitable ECG signal in real-time. In this experiment, the normal ECG signal for 15 minutes consumes 10% of Android phone battery power. The ECG signal of one hour is divided into blocks with a length of 10 seconds in this experimental study. Every 10 seconds of ECG signal is processed with the proposed SSA Method for calculating the noise-free ECG Signal(' appropriate ')

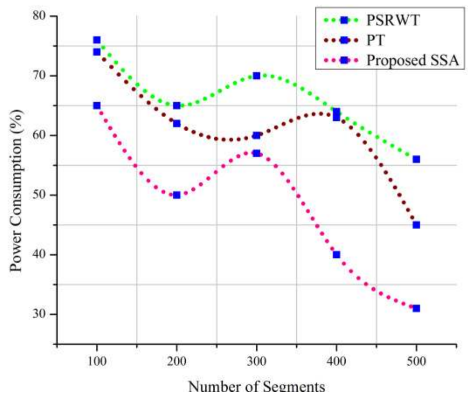



**FIGURE 9.** Power consumption.

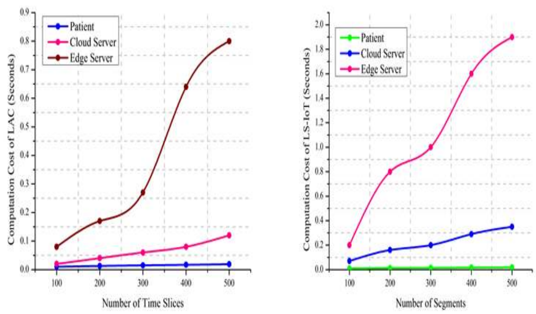



**FIGURE 10.** (a). The computation cost of LAC, (b) computation cost of LS-IoT.

and a noisy ECG Signal(' unsuitable'). For further clinical review and evaluation, the communication network is then activated to transmit ECG signal information to the cloud servers or other Android phones. The experimental results indicate that in only 241 quality segments of 360 ECG segments and 119 poor quality fields, including good and bad quality, the SSA method reduced energy consumption by 33% (Figure 9).

### D. COMPUTATION COST

Figure 10 (a) displays the patient, edge, and cloud service computational costs for LAC. In this algorithm, the patient doesn't need a calculation and the calculation costs are zero. Cloud server is used to provide storage evidence and edge server is used to verify storage proof. This sets N to 100 when this algorithm is simulated. With the rising number of time periods, the cost of computing cloud servers and edge servers is increasing. The Edge server needs to perform the pairing process, so it has a more litter than its cloud server computation. The edge server has a great computational capability at the edge of the network, and so computational costs for LAC are low and no external auditor is available.

The cloud server does not need a calculation in this algorithm and the expense for it is zero. The patient only needs health data to be encrypted and it uses simple additional processes to encrypt health data, which means that the patient's computational costs in LS-IoT are quite low.

Based on the above results and discussion, the proposed method which has better ECG Signal Strength Analysis for the automated classification and real-time implementation of IoT-assisted ECG monitoring system. The Lightweight Secure IoT (LS-IoT) and Lightweight Access Control (LAC) has better security and less computational cost while transmitting the ECG data.

## V. CONCLUSION AND FUTURE WORK

In this paper, a new ECG quality IoT-assisted signal analysis framework for applications of cardiac health surveillance is introduced. This paper provides an ECG-SSA methodology for the automated evaluation of the quality of ECG signals obtained in the sense of patient and physical activity. Results from experiments show that the suggested ECG-SQA is equivalent to other existing methods on the basis of morphological and RR interval and machine learning strategies. The analysis shows that the ECG signals are severely corrupted during increased physical activities. However, real-time evaluation results show that the proposed light-weight ECG Signal Strength Analysis (SSA) decreases the battery energy consumption considerably by transmitting appropriate ECG signals in IoT devices in unacceptable ECG signals. The Lightweight Secure IoT (LS-IoT) and Lightweight Access Control (LAC) which have better security for ECG data transmission. From this study, the ECG Signal Strength Analysis (SSA) implementation with a cardiac health control enabled IoT device has tremendous potential for improving the resource effectiveness, security and reliability of non-controlled signal analyzes and diagnostic systems through a reduction of false alarm levels for significant ECG noise recordings. In the future, the ECG health monitoring will be improved based on advanced machine learning algorithms.

## REFERENCES

[1] P. Verma and S. K. Sood, "Cloud-centric IoT based disease diagnosis healthcare framework," *J. Parallel Distrib. Comput.*, vol. 116, pp. 27–38, Jun. 2018.

[2] M. Bhatia and S. K. Sood, "A comprehensive health assessment framework to facilitate IoT-assisted smart workouts: A predictive healthcare perspective," *Comput. Ind.*, vols. 92–93, pp. 50–66, Nov. 2017.

[3] P. P. Ray, "Internet of Things based physical activity monitoring (PAMIoT): An architectural framework to monitor human physical activity," in *Proc. IEEE CALCON*, Kolkata, India, Nov. 2014, pp. 32–34.

[4] K. R. Darshan and K. R. Anandakumar, "A comprehensive review on usage of Internet of Things (IoT) in healthcare system," in *Proc. Int. Conf. Emerg. Res. Electron., Comput. Sci. Technol. (ICERECT)*, Dec. 2015, pp. 132–136.

[5] M. Hossain, S. M. R. Islam, F. Ali, K.-S. Kwak, and R. Hasan, "An Internet of Things-based health prescription assistant and its security system design," *Future Gener. Comput. Syst.*, vol. 82, pp. 422–439, May 2018.

[6] M. Neyja, S. Mumtaz, K. M. S. Huq, S. A. Busari, J. Rodriguez, and Z. Zhou, "An IoT-based E-Health monitoring system using ECG signal," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, Dec. 2017, pp. 1–6.

[7] P. M. Shakeel, S. Baskar, V. R. S. Dhulipala, S. Mishra, and M. M. Jaber, "Maintaining security and privacy in health care system using learning based deep-Q-networks," *J. Med. Syst.*, vol. 42, no. 10, p. 186, Oct. 2018, doi: 10.1007/s10916-018-1045-z.

[8] D. Azariadi, V. Tsoutsouras, S. Xydis, and D. Soudris, "ECG signal analysis and arrhythmia detection on IoT wearable medical devices," in *Proc. 5th Int. Conf. Mod. Circuits Syst. Technol. (MOCAST)*, May 2016, pp. 1–4.
[9] H. Mora, D. Gil, R. M. Terol, J. Azorín, and J. Szymanski, "An IoT-based computational framework for healthcare monitoring in mobile environments," *Sensors*, vol. 17, no. 10, p. 2302, 2302.
[10] M. Jiang, T. N. Gia, A. Anzanpour, A.-M. Rahmani, T. Westerlund, S. Salantera, P. Liljeberg, and H. Tenhunen, "IoT-based remote facial expression monitoring system with sEMG signal," in *Proc. IEEE Sensors Appl. Symp. (SAS)*, Apr. 2016, pp. 1–6.
[11] P. Singh and A. Jasuja, "IoT based low-cost distant patient ECG monitoring system," in *Proc. Int. Conf. Comput., Commun. Automat. (ICCCA)*, May 2017, pp. 1330–1334.
[12] Z. Yang, Q. Zhou, L. Lei, K. Zheng, and W. Xiang, "An IoT-cloud based wearable ECG monitoring system for smart healthcare," *J. Med. Syst.*, vol. 40, no. 12, p. 286, Dec. 2016.
[13] M. S. Islam, M. T. Islam, A. F. Almutairi, G. K. Beng, N. Misran, and N. Amin, "Monitoring of the human body signal through the Internet of Things (IoT) based LoRa wireless network system," *Appl. Sci.*, vol. 9, no. 9, p. 1884, 1884.
[14] S. Baskar, V. R. S. Dhulipala, P. M. Shakeel, K. P. Sridhar, and R. Kumar, "Hybrid fuzzy based spearman rank correlation for cranial nerve palsy detection in MIoT environment," *Health Technol.*, vol. 10, no. 1, pp. 259–270, Jan. 2020.
[15] D. Sobya, S. K. Muruganandham, S. Nallusamy, and P. S. Chakraborty, "Wireless ECG monitoring system using IoT based signal conditioning module for real time signal acquisition," *Indian J. Public Health Res. Develop.*, vol. 9, no. 5, pp. 294–299, 2018.
[16] R. L. Devi and V. Kalaivani, "Machine learning and IoT-based cardiac arrhythmia diagnosis using statistical and dynamic features of ECG," *J. Supercomput.*, pp. 1–12, May 2019, doi: 10.1007/s11227-019-02873-y.
[17] S. Howlader and S. B. Rao, "Real time signal quality aware ECG telemetry for IoT based health care monitoring system," *Int. J. Res.*, vol. 6, no. 8, pp. 165–173, 2019.
[18] A. M. Khairuddin, K. N. F. K. Azir, and P. E. Kan, "Limitations and future of electrocardiography devices: A review and the perspective from the Internet of Things," in *Proc. Int. Conf. Res. Innov. Inf. Syst. (ICRIIS)*, Jul. 2017, pp. 1–7.
[19] A.-M. Rahmani, N. K. Thanigaivelan, T. N. Gia, J. Granados, B. Negash, P. Liljeberg, and H. Tenhunen, "Smart e-Health gateway: Bringing intelligence to Internet-of-Things based ubiquitous healthcare systems," in *Proc. 12th Annu. IEEE Consum. Commun. Netw. Conf. (CCNC)*, Jan. 2015, pp. 826–834.
[20] R. B. Chukka and C. S. Kumar, "A novel architecture for the realisation of IoT-enabled ECG signal quality assessment using wavelet decomposition for baseline wander removal," *Sci. Technol. Res. Inst. Defence*, vol. 181, p. 192, Nov. 2018.
[21] U. U. Deshpande and M. A. Kulkarni, "IoT based real time ecg monitoring system using cypress WICED," *Int. J. Adv. Res. Elect., Electron. Instrum. Eng.*, vol. 6, no. 2, pp. 710–720, 2017.
[22] A. Vishwanatham, N. Ch, S. R. Abhishek, R. R. Chaitanya, S. S. S. Sanagapati, and S. Mohanty, "Smart and wearable ECG monitoring system as a point of care (POC) device," in *Proc. IEEE Int. Conf. Adv. Netw. Telecommun. Syst. (ANTS)*, Dec. 2018, pp. 1–4.
[23] J. Zhang, R. Sun, S. Wang, and J. Zhang, "The design of seven-lead electrocardiograph monitoring system based on Wi-Fi," in *Proc. 11th Int. Congr. Image Signal Process., Biomed. Eng. Informat. (CISP-BMEI)*, Oct. 2018, pp. 1–5.
[24] N. Clark, E. Sandor, C. Walden, I. S. Ahn, and Y. Lu, "A wearable ECG monitoring system for real-time arrhythmia detection," in *Proc. IEEE 61st Int. Midwest Symp. Circuits Syst. (MWSCAS)*, Aug. 2018, pp. 787–790.
[25] C. Liu, X. Zhang, L. Zhao, F. Liu, X. Chen, Y. Yao, and J. Li, "Signal quality assessment and lightweight QRS detection for wearable ECG SmartVest system," *IEEE Internet Things J.*, vol. 6, no. 2, pp. 1363–1374, Apr. 2019.
[26] J. Wannenburg, R. Malekian, and G. P. Hancke, "Wireless capacitive-based ECG sensing for feature extraction and mobile health monitoring," *IEEE Sensors J.*, vol. 18, no. 14, pp. 6023–6032, Jul. 2018.

**GUANGYU XU** was born in Inner Mongolia, China, in 1978. He received the B.S. degree in computer science and technology from Inner Mongolia Normal University, in 2002, and the M.S. degree in information engineering from the Inner Mongolia University of Technology, China, in 2006. He is currently a Lecturer and the Deputy Director of the Basic Teaching Department, School of Computer Information Management. He has published 13 articles and holds 2 patents. His research interests include big data, data mining, and the Internet of Things.